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Table of Contents

List of Tables

List of Charts and Figures

Abstract

Economic development incentives (EDI) have been widely used by state and local governments over the past three decades. They are viewed as an important tool to attract business investment, create jobs and ultimately stimulate economic growth. Despite extensive research on this topic, however, no consensus has been reached regarding the efficacy of such policies. This dissertation evaluates existing literature, explores a new database, and provides empirical contributions to research on EDI. Findings of this research are of direct interest to policymakers.

Chapter 1 surveys the empirical literature on EDI and discusses major EDI data sources. It summarizes EDI use at the state level based on the Subsidy Tracker database, which is subsequently used for the empirical research throughout the rest of this dissertation. Some highlights of the database include the following. Overall, there has been a proliferation of EDI use in all regions in the US, but states differ greatly in EDI utilization. Generally, the number of programs is a poor representation of states' EDI efforts. Aggregately, the South Region outspends the rest of the US even though the Midwest Region offers the most programs. Among different types of EDI, tax credits/rebates dominate, followed by grants/low cost loans.

Chapter 2 investigates whether EDI spending crowds out public expenditures in U.S. states. The possible under-provision of public goods as a downside of incentive use has long been noted as a major concern in both academic and media outlets. Empirical evidence addressing this issue, however, has been scanty. Exploiting the Subsidy Tracker database, this chapter contributes to the existing literature in several ways. First, I use state-level panel data that allows for more generalizable analysis compared with

case studies focusing on one program in a single geographic location. Second, this chapter investigates the effect of incentives on public goods provision at the state level instead of local level (county or city). Previous literature emphasizes that incentives may have different effects at the state level versus local level (Peters and Fisher, 2004), but empirical work primarily focuses on the local level. Third, the Generalized Method of Moments approach is employed to account for dynamic features associated with public expenditures. Potential endogeneity of policy variables and problems with unbalanced panels are also addressed. The specification uses lags of EDI values to accommodate possible delayed responses. Results show relatively little effect of EDI on most public goods expenditures in the first two time periods (including the current year) with negative repercussions beginning to appear in year two and provide some evidence of crowding out of productive public goods. Considering the important role productive public goods play in the state's long term growth, my results should serve as a warning to policymakers who contemplate using EDI programs to stimulate the economy.

Chapter 3 employs spatial econometric techniques to estimate the extent of strategic interaction in states' EDI spending decisions. Using a national search engine for EDI utilization, it is the first to examine strategic interaction in incentives use at the state level. It extends existing literature by exploiting panel data across states and by allowing for different definitions of neighbors to explore different EDI competition patterns across states. Results from 22 states during the period 2000 to 2011 indicate the presence of strategic interaction: states increase their EDI spending when their neighbors do so. The estimates range from 37 cents to 81 cents increases in EDI spending per dollar increase in neighbor's EDI spending and are robust to numerous checks. Further, interstate competition in EDI spending does not seem to get more intense after the 2008 financial crisis, nor does it seem to be affected by state governor election cycles.

Chapter 4 provides a preliminary examination of the relationship between EDI spending and state level income inequality. Results from dynamic panel methods indicate that EDI use is positively associated with the income share of top percentile. This poses a caveat to policymakers as EDI use could be linked to widening income inequality which could offset other possible benefits associated with EDI programs. Extensions for future research are discussed at the end of the chapter.

Chapter 1: Overview of Economic Development Incentives (EDI): Literature and Data

1.1 EDI Literature

Politicians are constantly pressured to stimulate local economic growth through the use of economic development incentives (EDI). The popularity of EDI can be attributable in part to its perceived benefits: higher business investment, job creation and economic growth. Despite decades of research on EDI, the efficacy of such policies is not well established in the literature.

Case studies abound in EDI literature. Despite being informative and in depth, one big disadvantage about case studies is the lack of generalizability. The results typically lack external validity due to idiosyncrasies of the program or location. Table 1.1 provides a summary of major case studies.

In addition to case studies, there is also literature on specific types of EDI programs, such as Tax Increment Financing (TIF) and enterprise zone (EZ) programs. Felix and Hines (2013) examine the characteristics associated with U.S. communities that offer tax-based business development incentives. In particular, they investigate what types of communities are more likely to use TIF, while Man (1999) and Byrne (2005) allow for policy interaction in modelling communities' decision to adopt TIF. Focusing on Chicago metropolitan area, Dye and Merriman (2000) find that municipalities adopting TIF grow more slowly compared with those that do not. Ladd (1994) discusses EZ programs including a review of case studies with the conclusion that enterprise zones are not a cost-effective way to stimulate employment. Bondonion and Greenbaum (2007) employ establishment level data across states to explore the growth impacts of EZ policy. Their results indicate that the positive impacts of EZ policies are counteracted by losses incurred.

Existing empirical studies mainly focus on evaluating employment, earning, and growth effects of EDI (Peters and Fisher, 2004; Patrick, 2012). The efficacy of EDI is less well represented in the literature. Two recent papers are Greenstone and Moretti (2003) and Patrick (2012). The former analyzes the effects of winning large industrial plants on local economies and fails to find decreases on important public goods expenditures by using data at the county level. Using matching strategy to study the fiscal effects of million dollar plants on county budgets, Patrick (2012) finds evidence of more spending on services by winning counties. The increase in debt, however, indicates service improvements are funded by borrowing and, hence, there is no evidence of fiscal surplus. Please refer to Table 1.2 regarding key empirical studies on EDI in the US.

As impressive as these two studies are, it is important to examine state level tax incentives because they account for the majority of tax incentives since the Tax Reform Act of 1986 (Luger and Bae, 2005). Further, fiscal impacts of incentives at the state level are likely to be different from that at the local level. Incentives are more likely to be marginally effective among geographically adjacent areas because tax differences are more important when other costs are similar. Empirical studies agree to this point (Peters and Fisher, 2004).

This dissertation focuses on investigating the effects of EDI at the state level. Chapter 2 sets out to examine the effects of EDI on public goods provision in U.S., which is motivated by the criticism against EDI use due to possible "crowding out" effects on productive public goods (Rolnick and Burstein, 1995; Gorin, 2008). Chapter 3 extends previous work by evaluating strategic interaction as a factor in explaining state level EDI spending. Chapter 4 explores the relationship between EDI use and income inequality using U.S. data. The rest of the introductory chapter describes existing data sources for EDI research and provides graphical presentation of the Subsidy Tracker database, which is employed in the empirical studies from Chapter 2 through Chapter 4.

1.2 EDI Data Sources

1.2.1 Definition of Economic Development Incentives

Hellerstein and Coenen (1995) consider tax incentives as "any provision designed to encourage new or expanded business activity in the state that is not an inherent part of the tax structure.[1]" Buss (2001) adopts the same definition and further points out that "the entire class of direct and indirect government subsidies includes but is not limited to property tax abatements, tax exemptions, low interest loans, free real estate, firm specific infrastructure, and firm specific job training." Chi and Hofmann (2000) define business incentives as "public subsidies, including, but not limited to, tax abatement and financial assistance programs, designed to create, retain or lure businesses for job creation." They consider both tax incentives (any credits or abatements) and financial incentives (loans, grants, infrastructure development or job training assistance), which is in line with the work of Buss (2001). Bartik (2005) focuses on cash or near cash assistance incentives versus customized services. This

[1] General tax policies in a state, such as corporate income tax rates, personal income tax rates and general sales tax rates, are not considered as part of EDI.

dissertation adopts the broader definition of EDI. Following Fisher and Peters (2004), my research considers both tax and non-tax incentives. [2]

1.2.2 EDI Measures and Data Sources

It is well established in the literature that ideal measures for EDI are hard to obtain (Fisher and Peters, 1997; Patrick, 2012). Many of the earlier studies during the 1980s and 1990s are built on problematic data or use measures which inadequately reflect the activeness or intensity of EDI use. The number of programs on a state's books, for example, was used in a couple of studies as an estimate for the state's incentives effort. Very often, however, this measure misrepresents a state's or city's commitment to economic development and masks the generosity of the incentives provided. It is not uncommon for states to have inactive or unfunded programs on their books. Additionally, states may combine or divide programs without changing the generosity of incentives offered. Fisher and Peters (1997) points out that the number of programs offered by one state is close to useless as a summary measure of one state's or incentives effort.

State economic development agency spending is another commonly used measure in the research. The budget of a state's lead development agency, however, rarely manages to accurately indicate subsidies awarded to business. For one, development agency funds can be used for alternative purposes or non-economic activities. For another, incentives expenditures could come from sources other than the agency's budget even when an appropriation is necessary. Hence, state economic development agency spending is a poor and problematic indicator for state economic

[2] Fisher and Peters (2004) emphasize "the firm, not the employee or job seeker, is the initial recipient of the incentive."

development efforts (Gorin, 2008). Conclusions based on a measure such as this are suspectful. Notably, the data source for state economic development agency expenditures, i.e. the website for the National Association of State Development Agencies (NASDA), does not exist anymore.

More recent studies adopt better measures but generally restrict their attention to a particular program, certain geographical locations, or incentives to large plants opening. For the purpose of this dissertation which focuses on EDI use across states, it is not enough to consider EDI use at a particular location or to big plants only. Fortunately, Good Jobs First (GJF) provides Subsidy Tracker, the first national search engine on EDI.[3] This rich database draws from a variety of information sources and contains subsidy types, subsidy values, recipient company, awarding agency, state and year data. It includes 12 broad categories of both tax and non-tax incentive programs (tax credits/rebates, property tax abatements, megadeal, grants/low-cost loans, enterprise zones, tax increment financing, training reimbursements, cost reimbursements, infrastructure assistance, industrial revenue bonds, tax credits/rebates and grants, tax credits/rebates and property tax abatements).[4] It is the most comprehensive database of incentives available. Two aspects of this database need to be acknowledged. First, it is a work in progress, so data are continually added. Second, for programs that extend over multiple years or even decades, the value of the whole

[3] Subsidy Tracker database: http://www.goodjobsfirst.org/subsidy-tracker. GJF is a non-partisan, nonprofit organization that promotes accountability in economic development and smart growth for working families.

[4] For detailed description, please refer to Subsidy Tracker user guide: http://www.goodjobsfirst.org/subsidy-tracker-user-guide.

package was documented in the beginning year. In other words, the data are not allocated across time in the case of multi-year award amounts.[5]

There are two other sources that provide EDI information. The New York Times assembles a database on business incentives from several sources including state government agencies, Investment Consulting Associates (ICA), Good Jobs First (GJF), company financial filings, and Equilar.[6] For unidentified company recipients, they drew information from GJF and ICA. Available since December 1, 2012, it offers little additional information compared with GJF's Subsidy Tracker. Further, this database has not been updated to include new programs or additional information about historical programs.[7]

The Council for Community and Economic Research (C2ER) provides two databases related to EDI. The State Business Incentives is a directory of current incentive programs in each state: program name, program provider, program description and website link are provided. The directory does not provide amounts for each program nor does it contain historical information. The State Economic Development Program Expenditures Database includes budgetary information collected from state economic development agencies. It covers state expenses for economic development

[5] Harpel (2014) also has a detailed discussion about Subsidy Tracker. http://www.smartincentives.org/blogs/blog/14754093-good-jobs-first-and-subsidy-tracker-2-0.

[6] ICA's IncentivesMonitar database tracks major financial subsidies and incentives around the world. Its coverage starts from 2010 and is updated in real time. For more information, please go to http://www.icaincentives.com/.
Equilar gathers data from U.S. Securities and Exchange Commission (SEC) filings and facilitates data analysis for consulting firms, investors and corporate executives. Please refer to http://www.equilar.com/ for more information. Both databases require subscription.

[7] http://www.nytimes.com/interactive/2012/12/01/us/government-incentives.html?_r=0

purposes and beyond. [8] The consistency of these expense categories facilitates comparison across states and over time. Unfortunately, it covers only more recent years, since fiscal year 2007. This database currently updates biannually and can be a promising source for future research on EDI.

1.3 An Overview of EDI Use

This discussion below provides a brief description of how EDI use evolved over time and presents some regional characteristics from Subsidy Tracker updated on July 9th, 2013. All dollar figures have been converted to real values, deflated by CPI (1982-84=100).[9]

1.3.1 Incentives Use by States

Table 1.3 illustrates the coverage of subsidy tracker data. It includes 48 U.S. states and D.C. during the years 1976-2013. Hawaii and Wyoming are excluded due to lack of EDI spending data. Check marks represent EDI spending data for a specific state in a given year are available, while blanks mean either no program was documented in that specific state-year, or no subsidy value was detailed. A glimpse at the table indicates a few states have a lot more observations than the rest. North Dakota, Virginia, New York and Kentucky have more than 20 years of EDI spending data, while DC and Massachusetts have only three. In addition to differences in reporting and disclosure, the variation in coverage probably also indicates that states differ in their efforts in EDI use. The following Table 1.4 just summarizes the information from Table 1.3.

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[8] Please refer to C2ER website for more information (https://www.c2er.org/products/stateexpenditures.asp).
[9] Given that Subsidy Tracker is frequently updated, it is important to note the publication data.

Chart 1.1 portrays counts of subsidy programs versus per capita EDI spending in an attempt to see how well program counts reflect subsidy intensity.[10] When ranking states by the number of programs offered over sample period, we noticed great variation in EDI spending per capita even among states that offer few programs. EDI spending per capita goes from as little as less than 10 dollars in New Hampshire to as high as over 1000 dollars in Alaska and New Mexico. States that offer more programs like Wisconsin and Texas, however, do not necessarily outspend low program number states. A similar story appears in Chart 1.2 that shows number of programs against total EDI spending. The gist is that number of programs is a poor indicator of how active states are in their EDI spending.

The following two charts (1.3 and 1.4) display per capita EDI spending and total EDI spending by state, averaged over available years. There are dramatic changes in EDI spending across states. On a per capita basis, there are very active states like Alaska and Louisiana that spend more than 100 dollars per capita. Meanwhile, low spending states include Colorado, New Hampshire and Maryland. This great variation among states is also prevalent for total EDI spending as shown in Chart 1.5. In this case, New York, Michigan and Washington stand out as states that spend a lot while North Dakota and Montana are the low spending states.

The last three charts (1.5, 1.6 and 1.7) show how the counts of EDI programs and EDI spending (both in terms of per capita and total) have changed over time. In general, recent years has seen an increase in the number of programs offered by states before a notable dip in 2011. Per capita EDI spending has shown more of pro-business

[10] Per capita EDI spending is calculated as the summation of per capita EDI spending in each state over available years.

cyclical pattern, we see higher incentive spending during high growth years and low incentives spending associated during downturns like the early 1990s, mid 1990s and early 2000s. Total EDI spending has increased in general over time.

1.3.2 Regional Variation in EDI Use by Type

As demonstrated in the previous section, EDI use is prolific among U.S. states and states exhibit great variation in EDI use. This section breaks down EDI use by types and region to identify any pattern. Please refer to Table 1.5 regarding the classification of regions and division for U.S. states.

Figure 1.1 ranks the number of EDI programs offered from all states over all the available years from smallest to largest by type. Tax credit/rebate programs dominate the number of programs provided, followed by grant/low cost loans. These two types programs for 60% of all programs offered. Less commonly used types include infrastructure assistance, tax credit/rebate combined with grants, cash grants and industrial revenue bonds. From the pie chart, we can see that Megadeal, training reimbursement and property tax abatement constitutes 30% of all programs offered, while enterprise zones, tax increment financing and the other less commonly used EDI types only add up to 10%.

As mentioned before, program counts may not be a reliable measure for intensiveness of use. Hence, looking at the importance of each EDI type in terms of spending in real dollar values is more informative (Figure 1.2). Not surprisingly, Megadeals dominate other types (57%) because by definition Megadeal refers to packages 75 million dollars or more. In addition to Megadeals, tax credit/rebate and grants/low-cost loans account for a quarter of all programs in terms of EDI value.

Similar as before, infrastructure assistance, industrial revenue bonds, cash grants and cost reimbursements account for a very small proportion of total EDI spending over the years. The same patterns in data remain even if we take out programs classified as Megadeal.

When we break down EDI programs offered by four regions (Figure 1.3), the Midwest Region and South Region accounts for about a third of all programs offered respectively, and West Region offers about the same number of programs as Northeast Region. In terms of total spending (Figure 1.4), however, we see a different picture. The South Region outspends all the other regions, reaching over 20 billion dollars over the years and accounting for about a third of all EDI spending. The Midwest Region and Northeast Region each account for about a quarter of total EDI spending, whereas West Region occupies the smallest proportion.

Considering EDI patterns at the division level (Figure 1.5), there is variation within each region as well. Even though the Midwest Region offers the largest number of programs, the East North Central Division within it provides 50% more than the West North Central Division. The South Atlantic Division offers the most within South Region. The Mountain Division within West Region offers the fewest programs of all. In terms of real EDI spending (Figure 1.6), however, the Middle Atlanta Division outspends the rest, with about 14 billion dollars for a quarter of total spending. Next comes the East North Central Division, with about 17% of total spending. The New England Division and the Mountain division account for the smallest proportions, 3% and 5% respectively

1.4 Summary

This chapter provides an overview of the empirical literature on EDI and summarizes major data sources available for research. In particular, it documents EDI use at the state level including time trends, states comparison, and regional variation using data from GJF. The Subsidy Tracker database informs the analyses from Chapter 2 through Chapter 4. Some highlights of the database include the following.

Every state has at least one type of incentive programs and EDI spending by state and local governments reach billions of dollars collectively. Recent years have seen an increase in EDI spending except 2013. Overall, EDI remains a popular tool among policymakers in US.

The number of programs is a generally poor indicator of how active states are in their EDI use. In addition to Megadeals, tax credits/rebates dominate the use among different types of EDI, followed by grants/low cost loans and property tax abatements.

EDI use varies greatly across states. Active states like Louisiana and Alaska spend more than 100 dollars per capita on average over the years whereas Colorado and New Hampshire spend less than a dollar per capita. In the aggregate, the Midwest Region provides the largest number of EDI programs, but the South Region spends most.

Table 1.1: Summary of Major Case Studies on EDI

Study	Period	Region/Focus	Findings
Bartik and Erickcek (2012)	1995-2011	Michigan. Simulation of job and fiscal impacts of MEGA tax credit program	Greater fiscal and job creation benefits relative to cutting overall state business taxes
Weiner (2009)	2000s	New England state. Four types of tax credits	New revenues do not offset initial costs, i.e., most credits do not "pay for themselves"
Calcagno and Hefner (2008)	2006-2007	South Carolina. Film industry	Subsidies to film industry are a net loss to state revenue
Wong and Stiles (2007)	1989-2007	Kansas and five surrounding states. Multiple Programs	States prefer to use tax incentives rather than direct subsidies to fund economic development.
Hoyt, Jepsen and Troske (2007)	1992-2004	Kentucky. Multiple Programs	Training incentives positively related to employment and earnings
Luger and Bae (2005)	1999	North Carolina. Simulation approach to study the effects of state business tax incentives	Not cost effective in inducing new employment
Goodman (2003)	1986-1999	Colorado. Sales tax	Benefits largely transferred to relocated business and migrants rather than local residents

Table 1.2: Summary of Key Empirical Studies on EDI

Study	Period	Level	Findings
Patrick (2012)	1977-1997	U.S. County	Winning counties spend more on services, but it is likely funded by borrowing than fiscal surplus
Greenstone and Moretti (2003)	1972-1992	U.S. County	No evidence of reduction in county government's budget and expenditures on important public services
O hUallachain and Satterthwaite (1992)	1977-1984	U.S. Metropolitan	Enterprise zones and university research parks are associated with increased job growth
de Bartolome and Spiegel (1997)	1990	U.S. State	State economic development expenditures positively correlated with manufacturing employment growth
Goss and Phillips (1997)	1986-1994	U.S. State	State economic development agency spending has a modest positive effect on the generation of state income and employment

Table 1.3: Subsidy Tracker Database (2013.07.09)

	AK	AL	AR	AZ	CA	CO	CT	DC	DE	FL	GA	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	Total
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2003				✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓			✓		✓	✓	✓			✓	✓			✓	✓	✓	✓	✓		✓						✓		✓	✓	✓		✓	28
2004				✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓			✓			✓	✓			✓	✓			✓	✓	✓	✓	✓		✓			✓			✓		✓	✓	✓			27
2005				✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓			✓		✓	✓	✓	✓		✓	✓			✓	✓	✓	✓	✓		✓					✓	✓		✓	✓	✓			30
2006				✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓			✓		✓	✓	✓		✓	✓	✓			✓	✓	✓	✓	✓		✓						✓		✓	✓	✓			30
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2008		✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	43
2009	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	45
2010		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	44
2011	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	46
2012	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓	42
2013	✓		✓	✓				✓		✓	✓						✓	✓		✓			✓		✓	✓	✓			✓	✓			✓	✓	✓				✓		✓								20
Total	10	12	4	13	12	13	20	3	16	19	13	16	13	25	11	9	28	6	3	17	7	15	16	13	8	8	12	23	6	7	18	12	12	27	18	7	15	7	6	6	5	11	17	7	22	15	9	6	6	604

Table 1.4: Summary of Subsidy Tracker Coverage

State	No. of Available Yrs	State	No. of Available Yrs
Alaska	10	Montana	8
Alabama	12	North Carolina	12
Arkansas	4	North Dakota	23
Arizona	13	Nebraska	6
California	12	New Hampshire	7
Colorado	13	New Jersey	18
Connecticut	20	New Mexico	12
DC	3	Nevada	12
Delaware	16	New York	27
Florida	19	Ohio	18
Georgia	13	Oklahoma	7
Iowa	16	Oregon	15
Idaho	13	Pennsylvania	7
Illinois	25	Rhode Island	6
Indiana	11	South Carolina	6
Kansas	9	South Dakota	5
Kentucky	28	Tennessee	11
Louisiana	6	Texas	17
Massachusetts	3	Utah	7
Maryland	17	Virginia	22
Maine	7	Vermont	15
Michigan	15	Washington	9
Minnesota	16	Wisconsin	6
Missouri	13	West Virginia	6
Mississippi	8		

Chart 1.1: Per Capita EDI Spending vs. Counts of EDI Programs

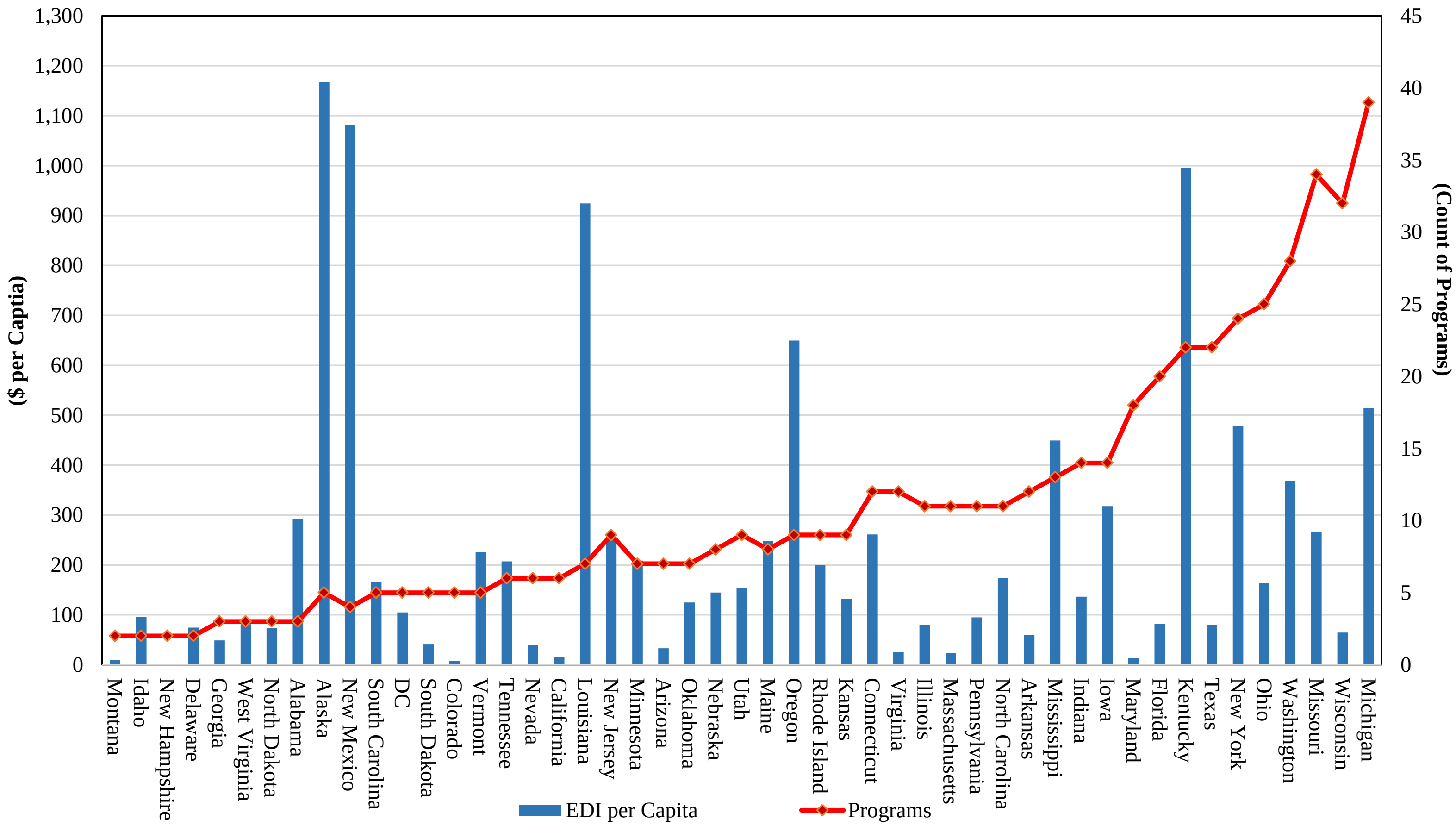


Chart 1.2: Total EDI Spending vs. Counts of EDI Programs

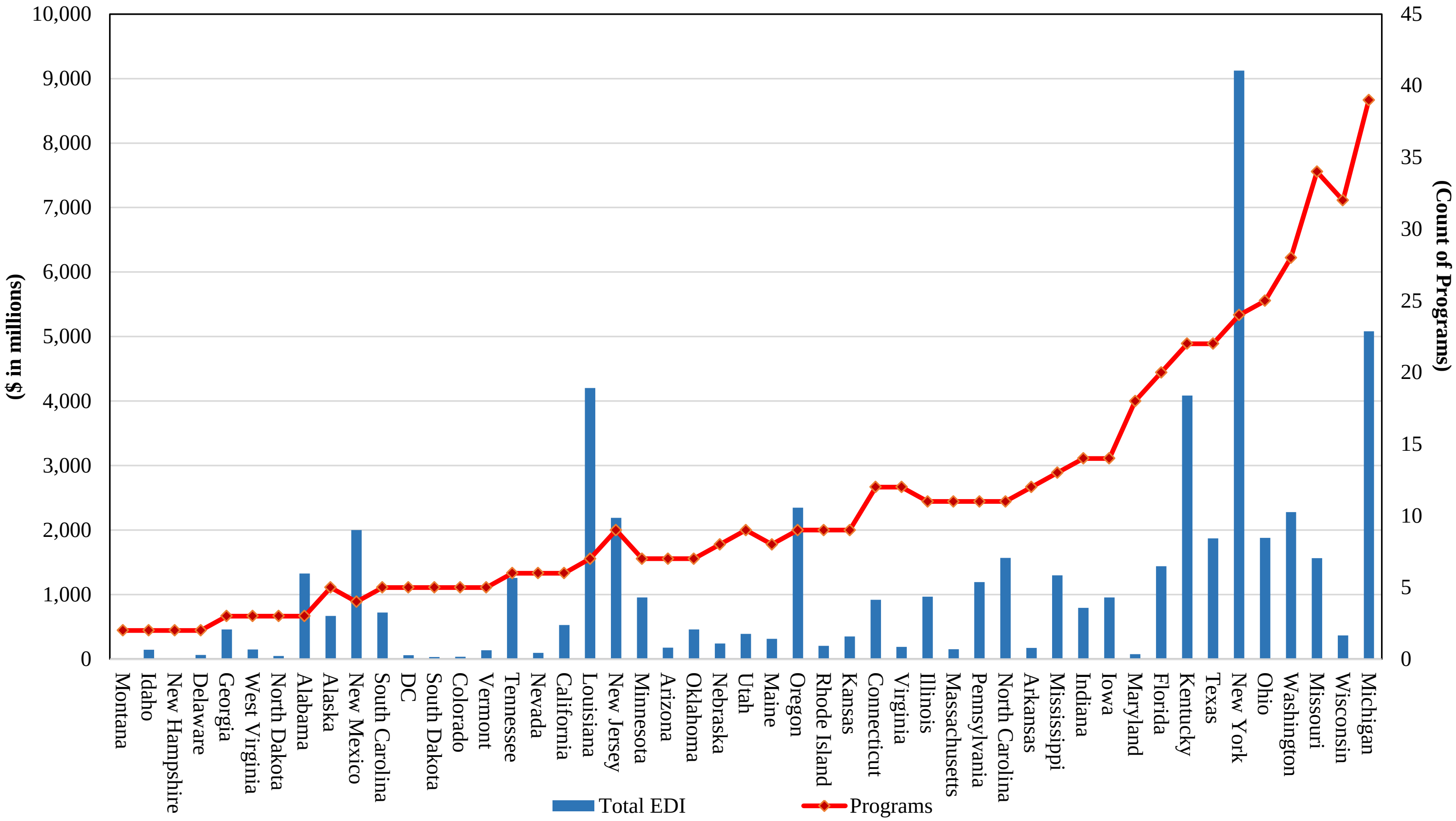


Chart 1.3: Per Capita EDI Spending by State, Average over Available Years ($)

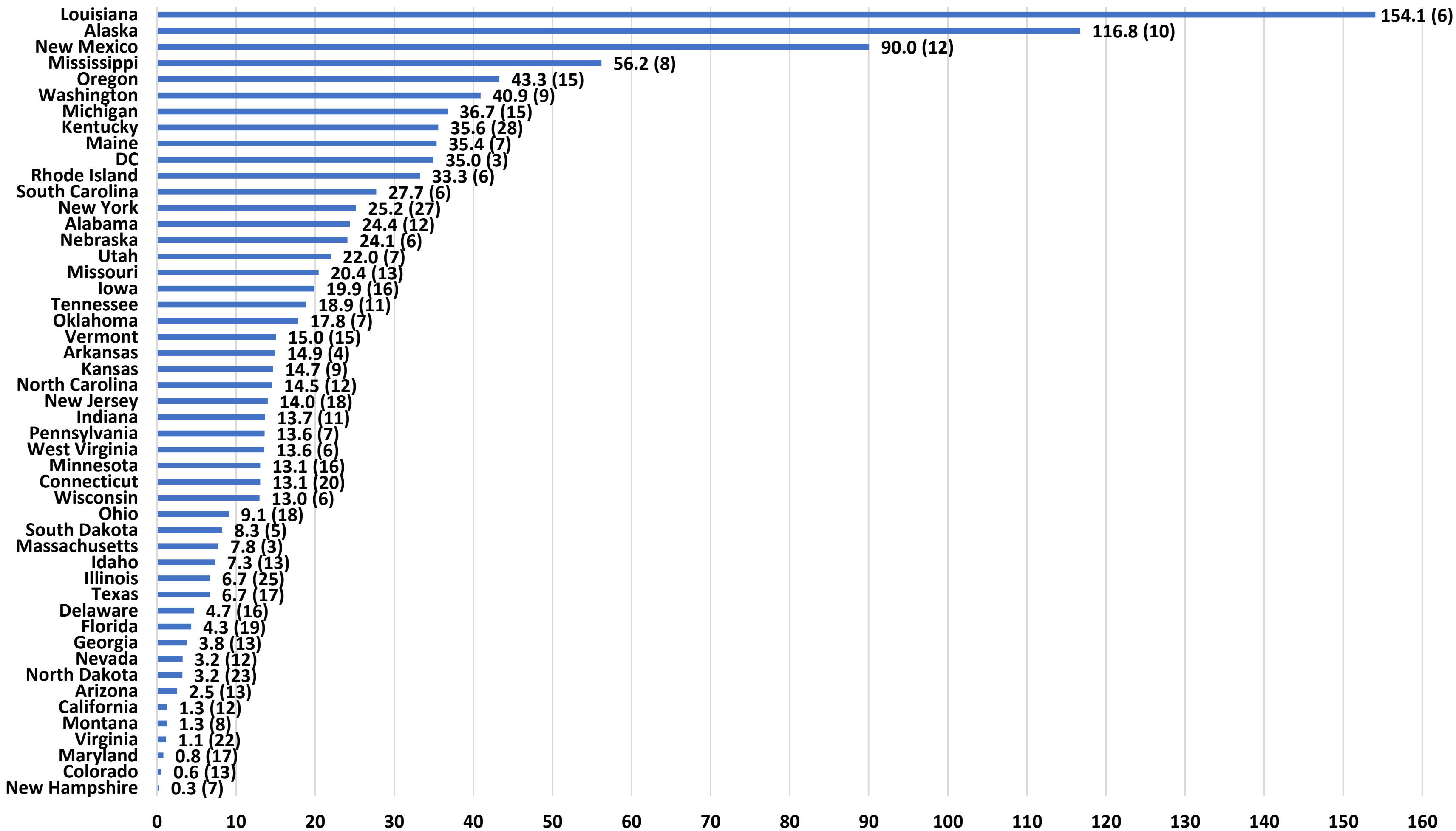


Chart 1.4: Total EDI Spending by State, Average over Available Years ($ in millions)

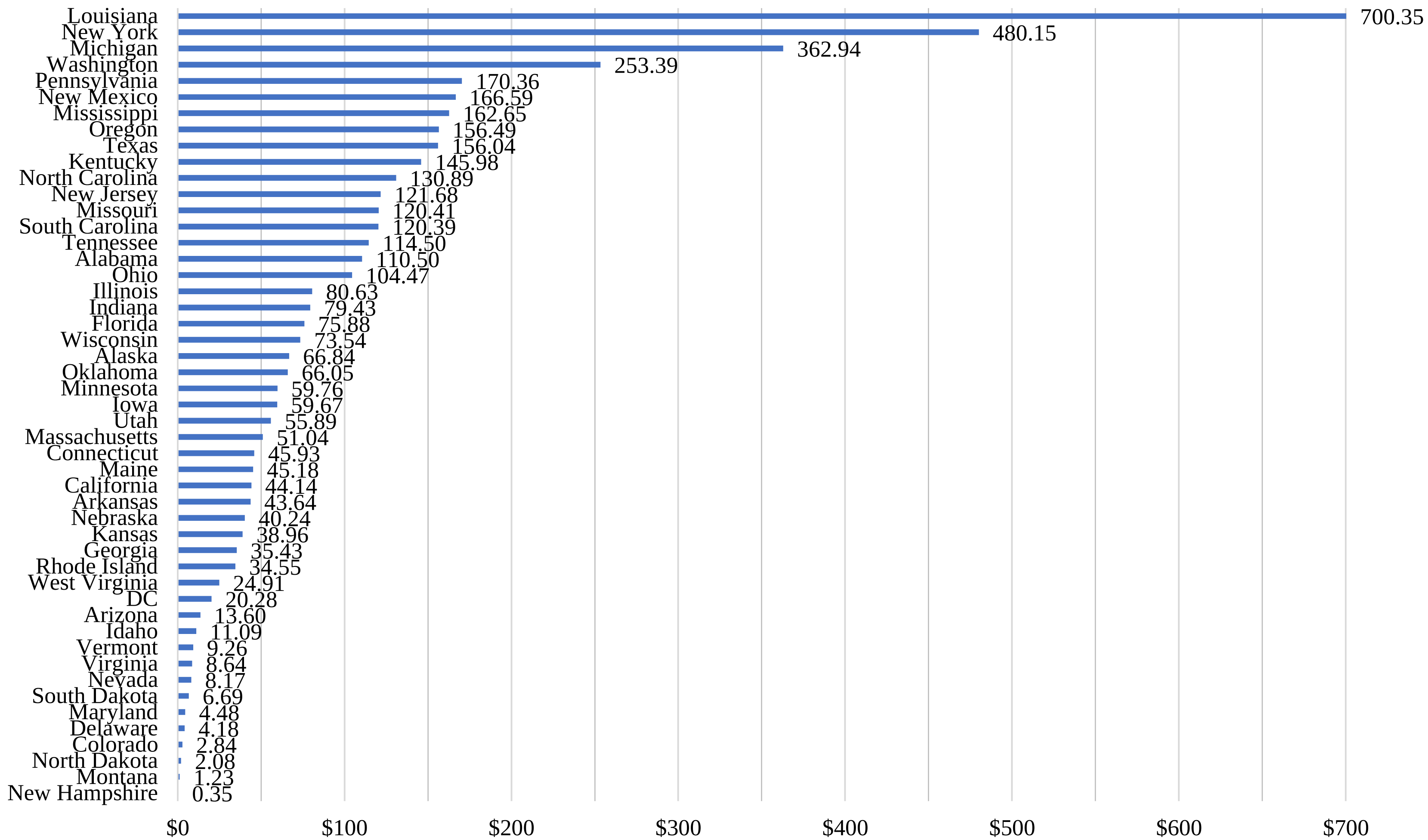


Chart 1.5: EDI Program Counts

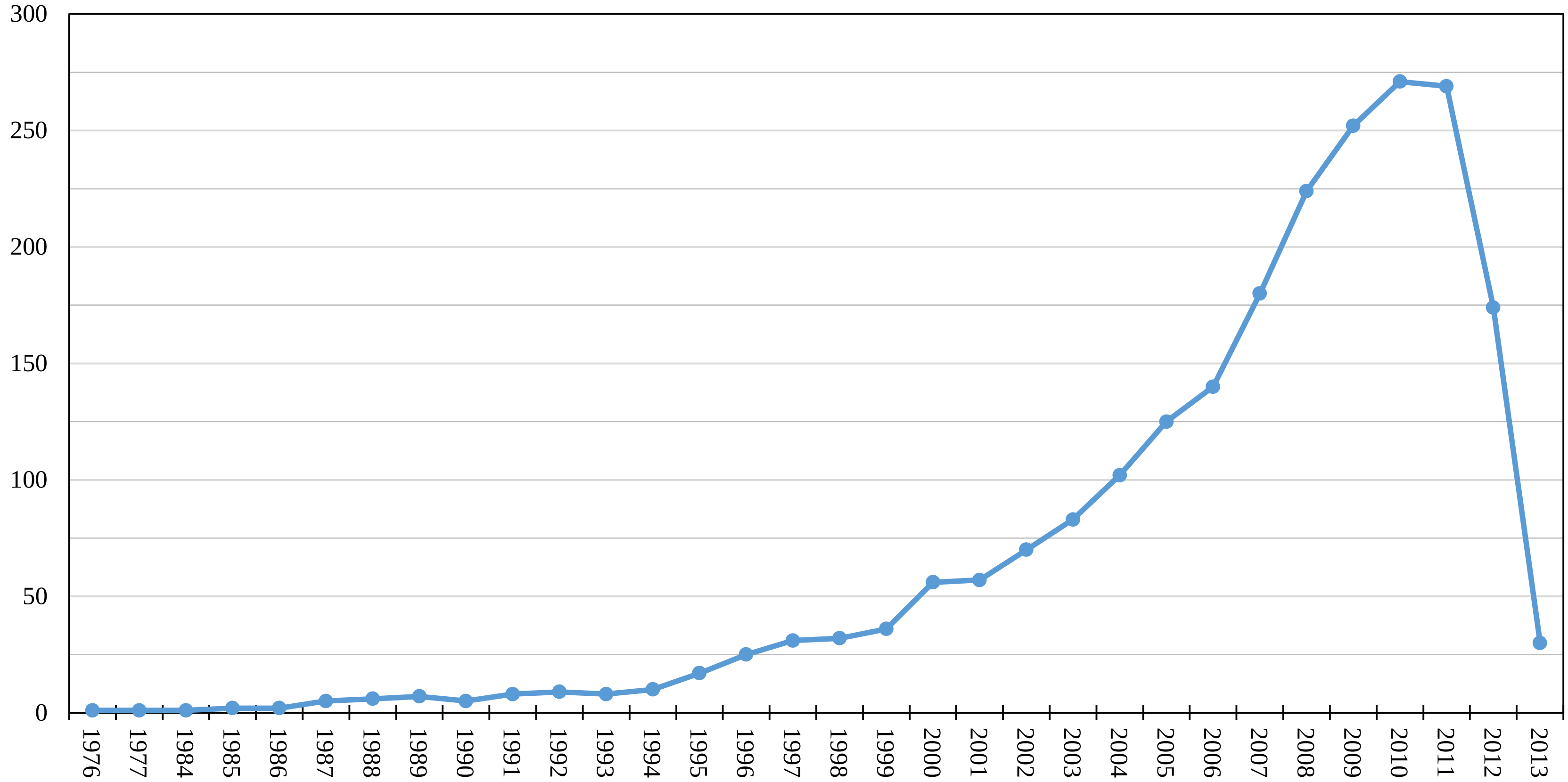


Chart 1.6: Per Capita EDI Spending ($)

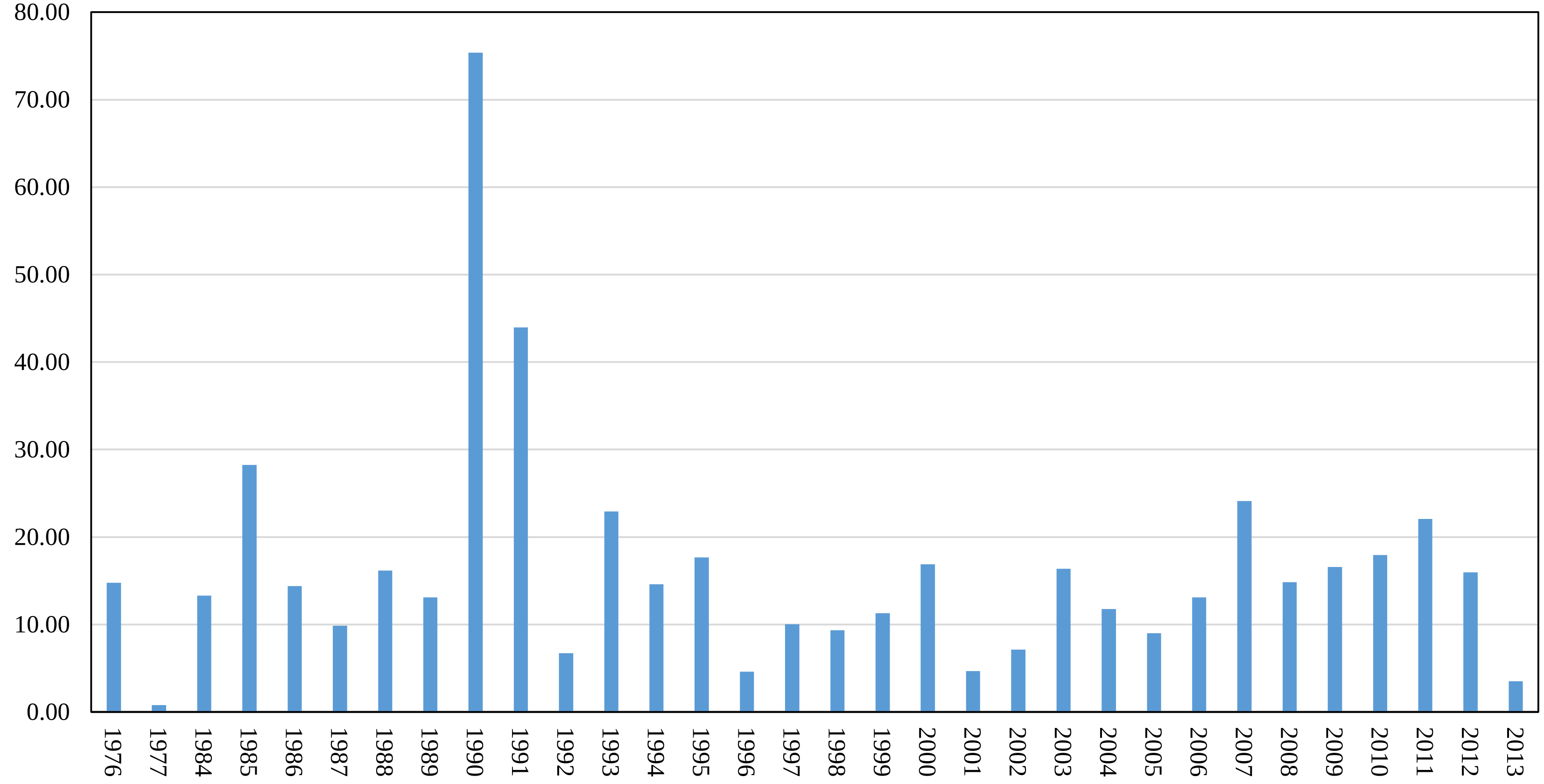


Chart 1.7: Total EDI Spending ($ in millions)

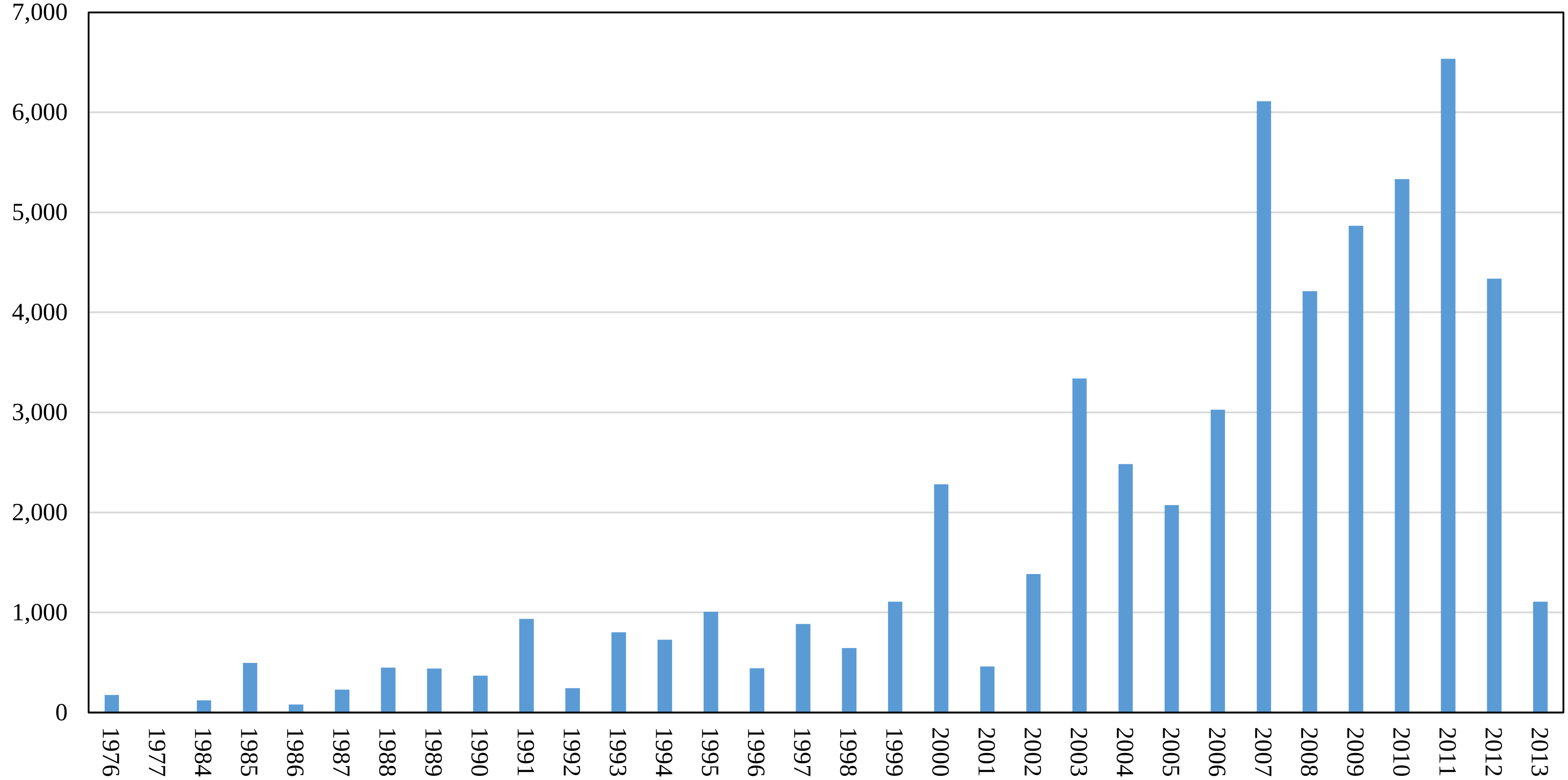
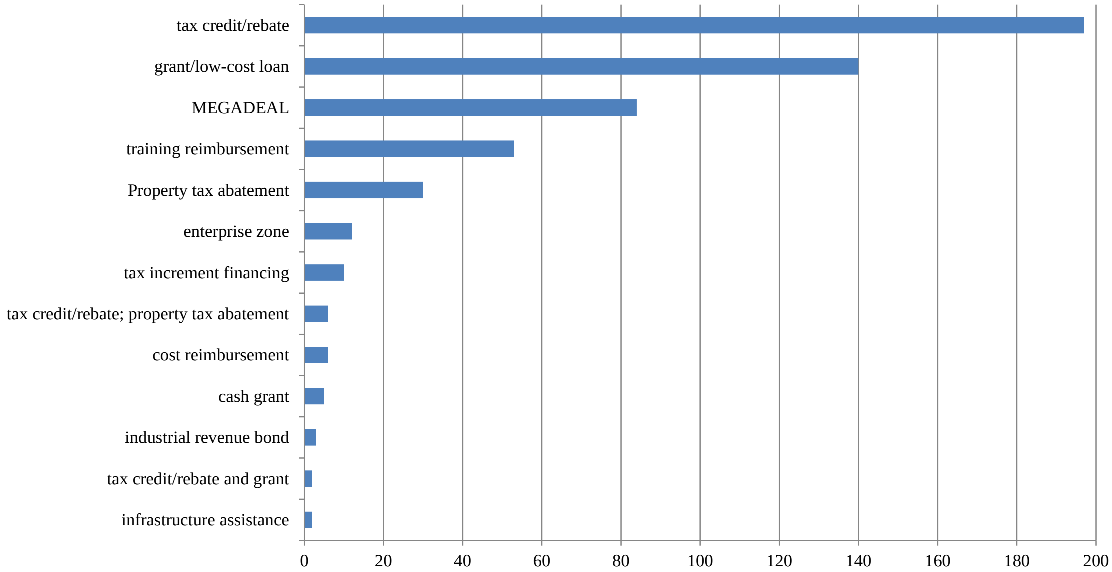


Table 1.5: U.S. States by Regions and Divisions[11]

State	Abbr.	Region	Division
Alabama	AL	South Region	East South Central Division
Alaska	AK	West Region	Pacific Division
Arizona	AZ	West Region	Mountain Division
Arkansas	AR	South Region	West South Central Division
California	CA	West Region	Pacific Division
Colorado	CO	West Region	Mountain Division
Connecticut	CT	Northeast Region	New England Division
DC	DC	South Region	South Atlantic Division
Delaware	DE	South Region	South Atlantic Division
Florida	FL	South Region	South Atlantic Division
Georgia	GA	South Region	South Atlantic Division
Hawaii	HI	West Region	Pacific Division
Idaho	ID	West Region	Mountain Division
Illinois	IL	Midwest Region	East North Central Division
Indiana	IN	Midwest Region	East North Central Division
Iowa	IA	Midwest Region	West North Central Division
Kansas	KS	Midwest Region	West North Central Division
Kentucky	KY	South Region	East South Central Division
Louisiana	LA	South Region	West South Central Division
Maine	ME	Northeast Region	New England Division
Maryland	MD	South Region	South Atlantic Division
Massachusetts	MA	Northeast Region	New England Division
Michigan	MI	Midwest Region	East North Central Division
Minnesota	MN	Midwest Region	West North Central Division
Mississippi	MS	South Region	East South Central Division
Missouri	MO	Midwest Region	West North Central Division
Montana	MT	West Region	Mountain Division
Nebraska	NE	Midwest Region	West North Central Division
Nevada	NV	West Region	Mountain Division
New Hampshire	NH	Northeast Region	New England Division
New Jersey	NJ	Northeast Region	Middle Atltantic Division
New Mexico	NM	West Region	Mountain Division
New York	NY	Northeast Region	Middle Atltantic Division
North Carolina	NC	South Region	South Atlantic Division
North Dakota	ND	Midwest Region	West North Central Division
Ohio	OH	Midwest Region	East North Central Division
Oklahoma	OK	South Region	West South Central Division
Oregon	OR	West Region	Pacific Division
Pennsylvania	PA	Northeast Region	Middle Atltantic Division
Rhode Island	RI	Northeast Region	New England Division
South Carolina	SC	South Region	South Atlantic Division
South Dakota	SD	Midwest Region	West North Central Division
Tennessee	TN	South Region	East South Central Division
Texas	TX	South Region	West South Central Division
Utah	UT	West Region	Mountain Division
Vermont	VT	Northeast Region	New England Division
Virginia	VA	South Region	South Atlantic Division
Washington	WA	West Region	Pacific Division
West Virginia	WV	South Region	South Atlantic Division
Wisconsin	WI	Midwest Region	East North Central Division
Wyoming	WY	West Region	Mountain Division

[11] Census Bureau: http://www.census.gov/econ/census07/www/geography/regions_and_divisions.html

Figure 1.1: Counts of EDI Programs by Type



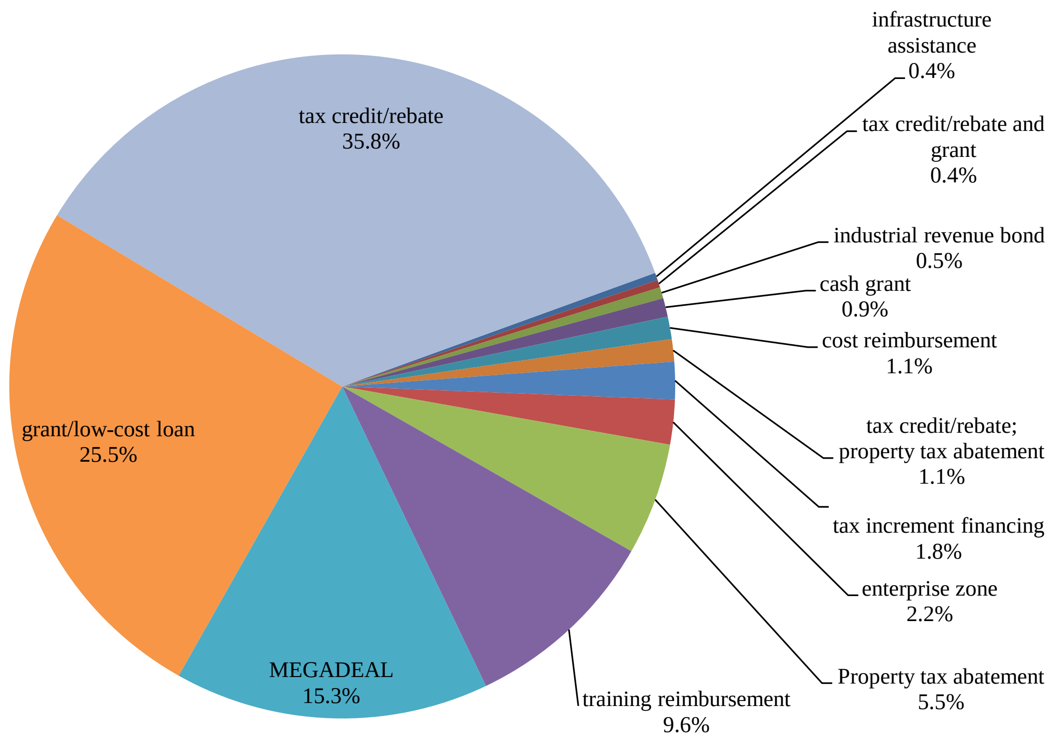
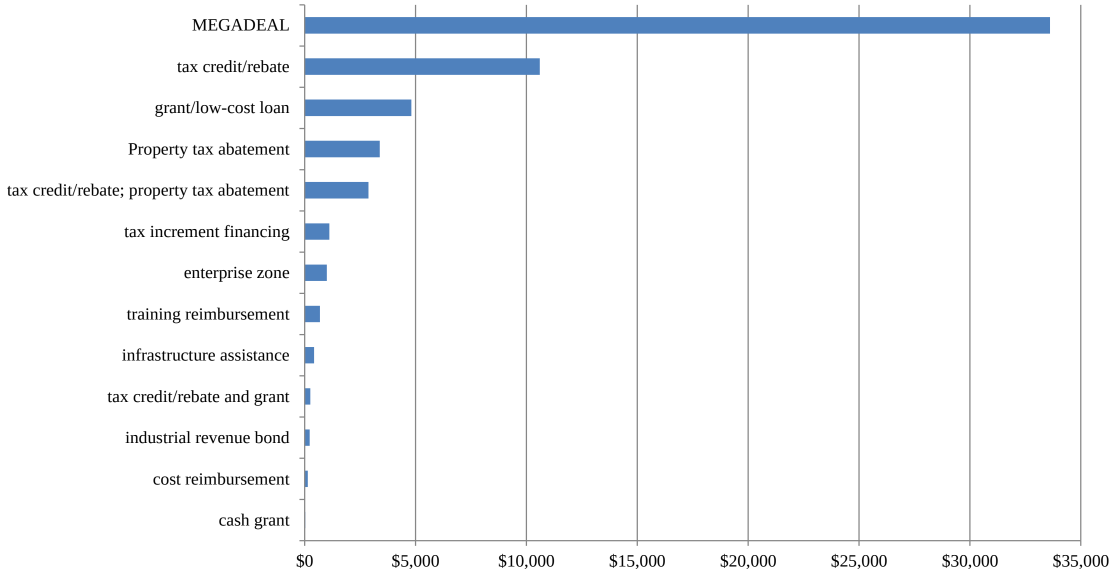


Figure 1.2: Real EDI Spending ($ in millions)



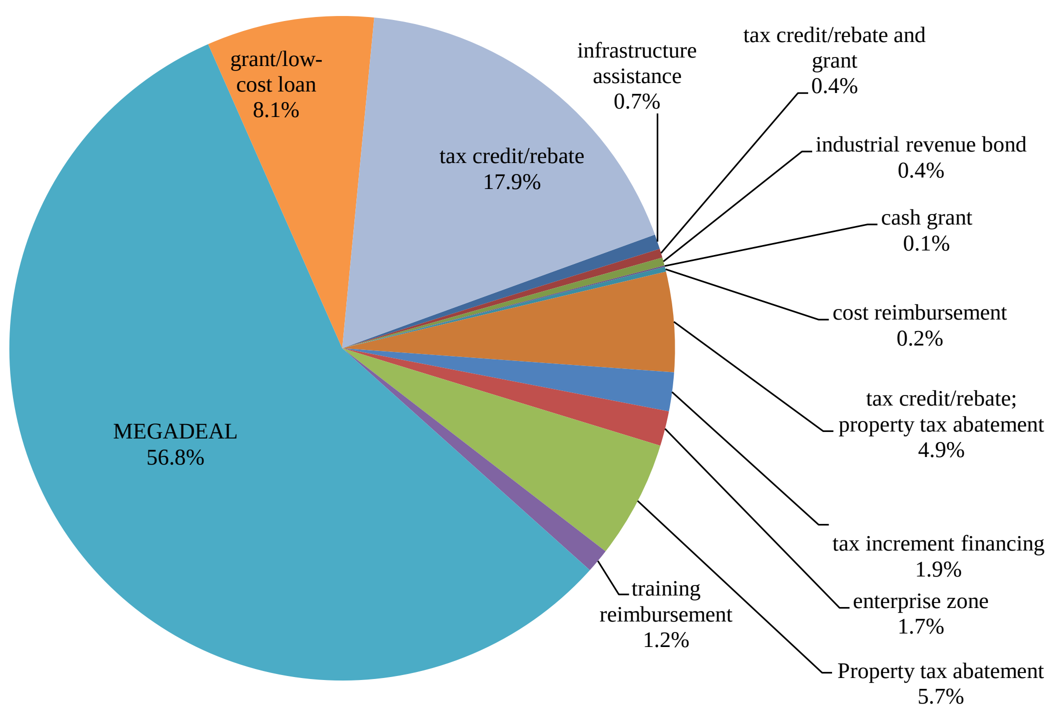
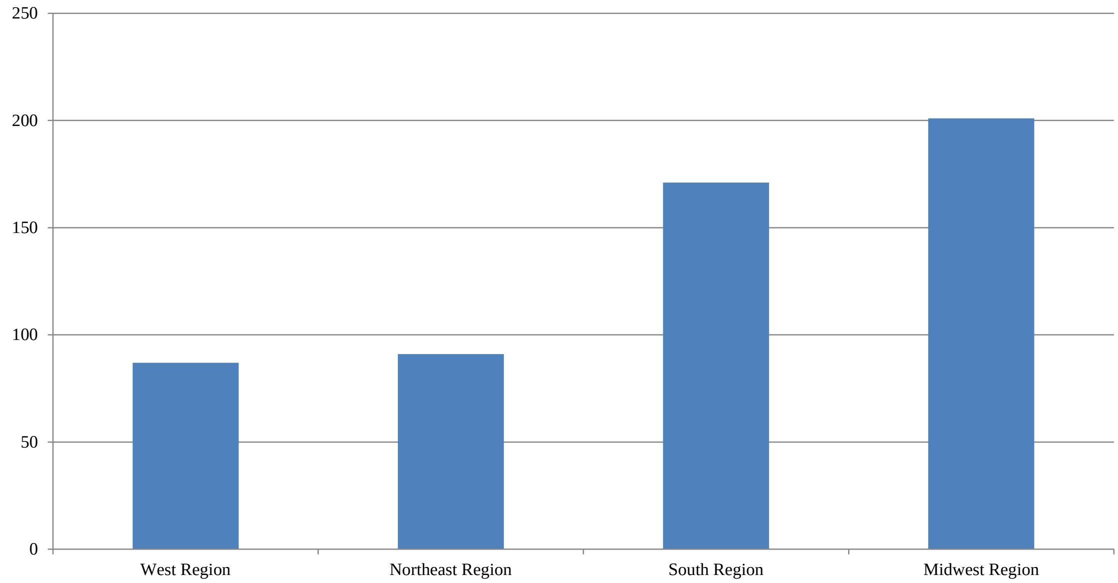


Figure 1.3: Counts of EDI Programs by Region



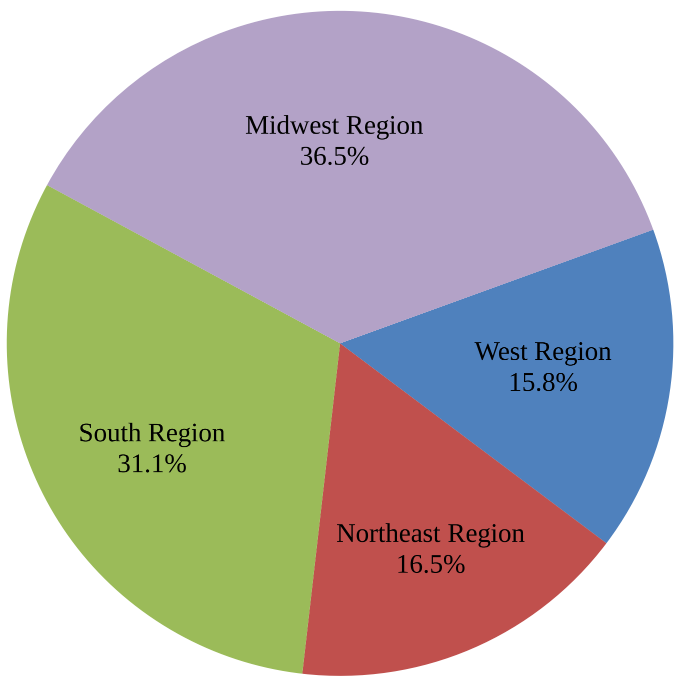
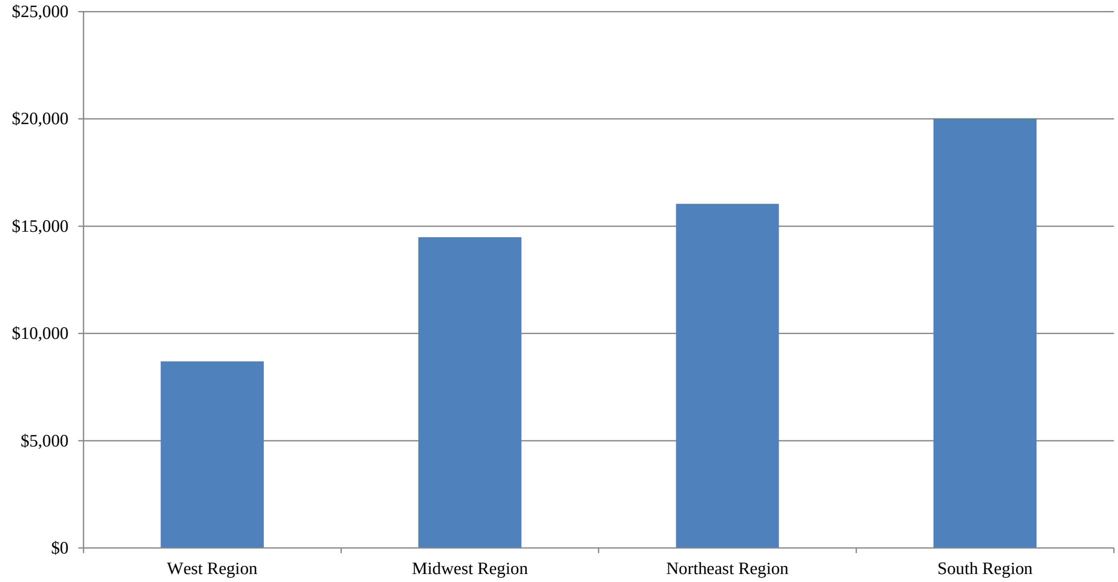


Figure 1.4: Real EDI Spending by Region ($ in millions)



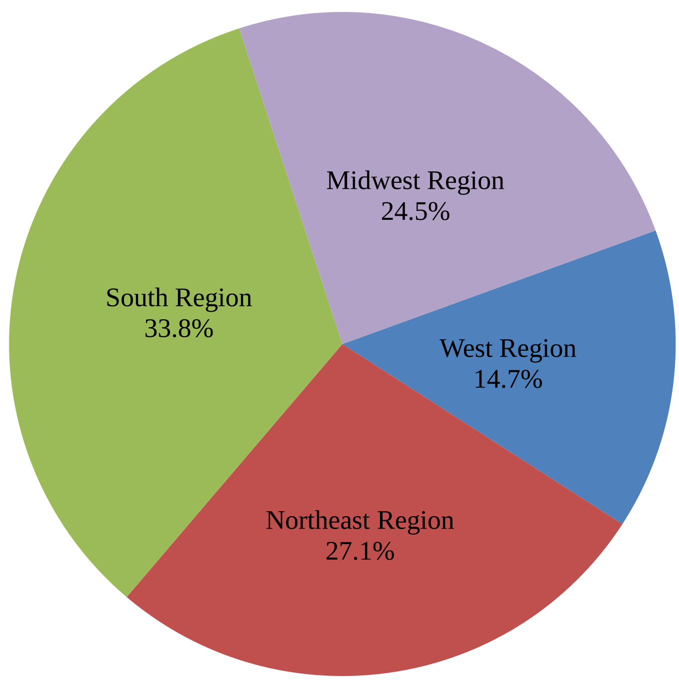
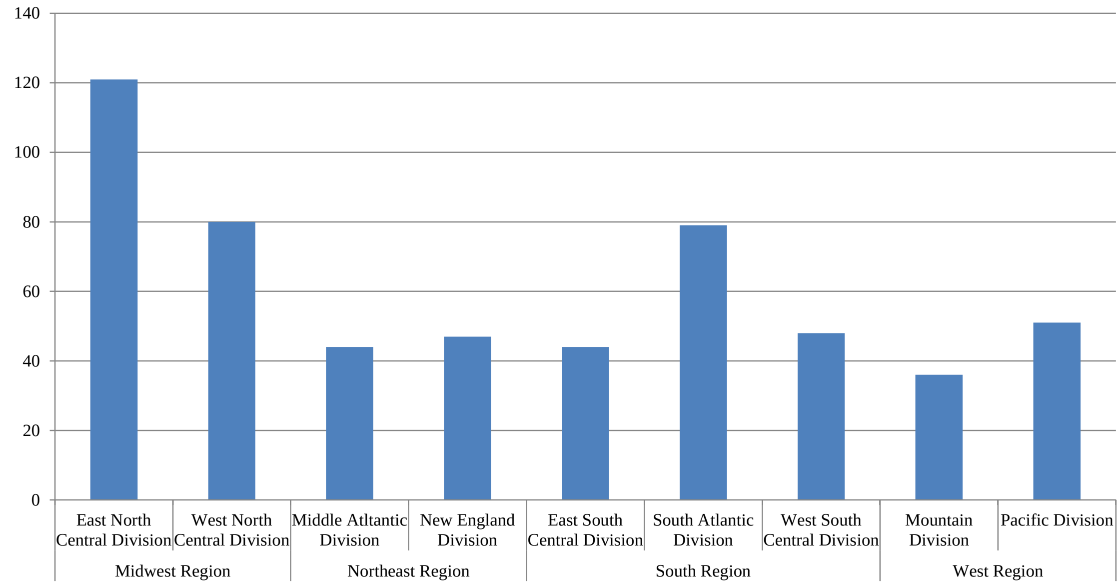


Figure 1.5: Counts of EDI Programs by Division



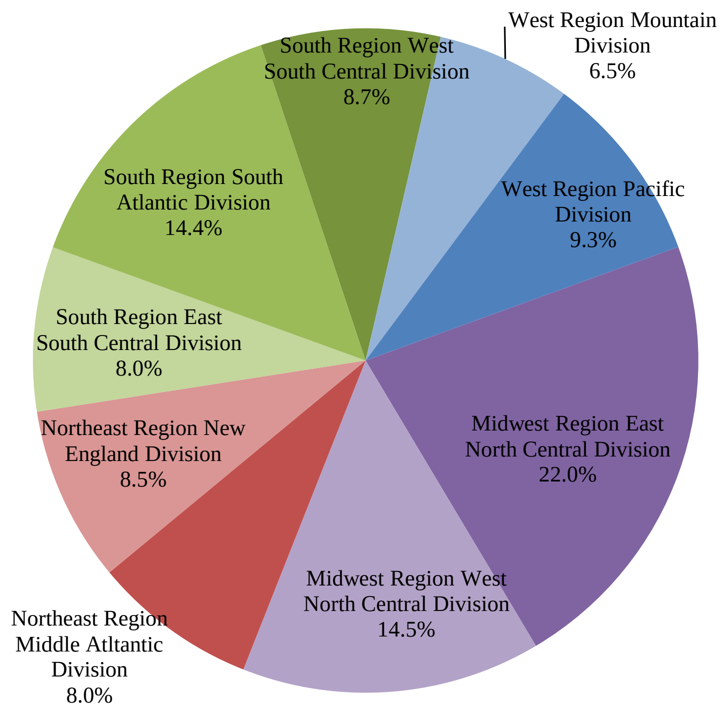
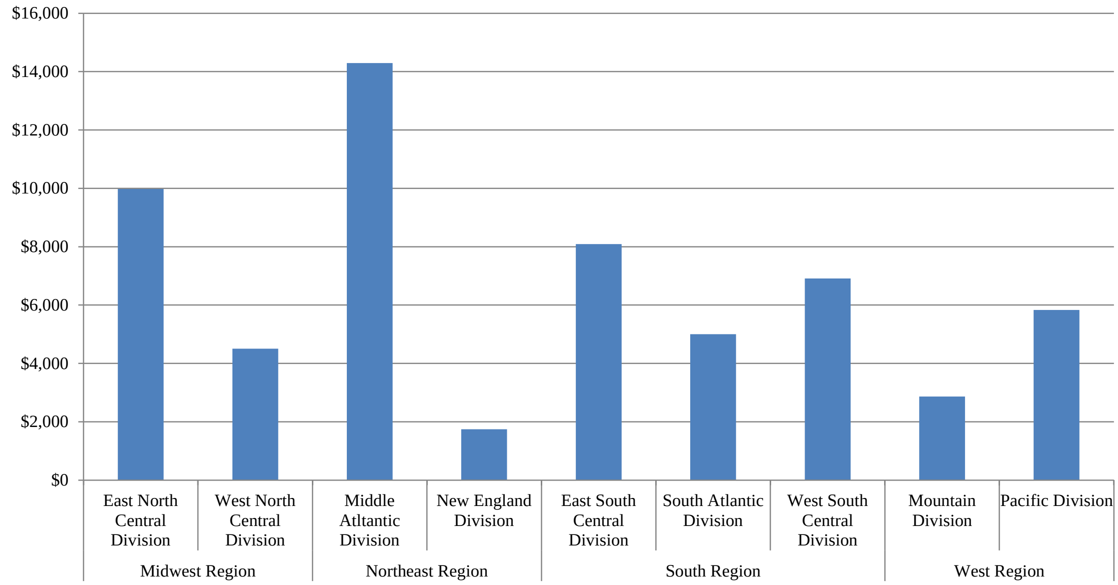
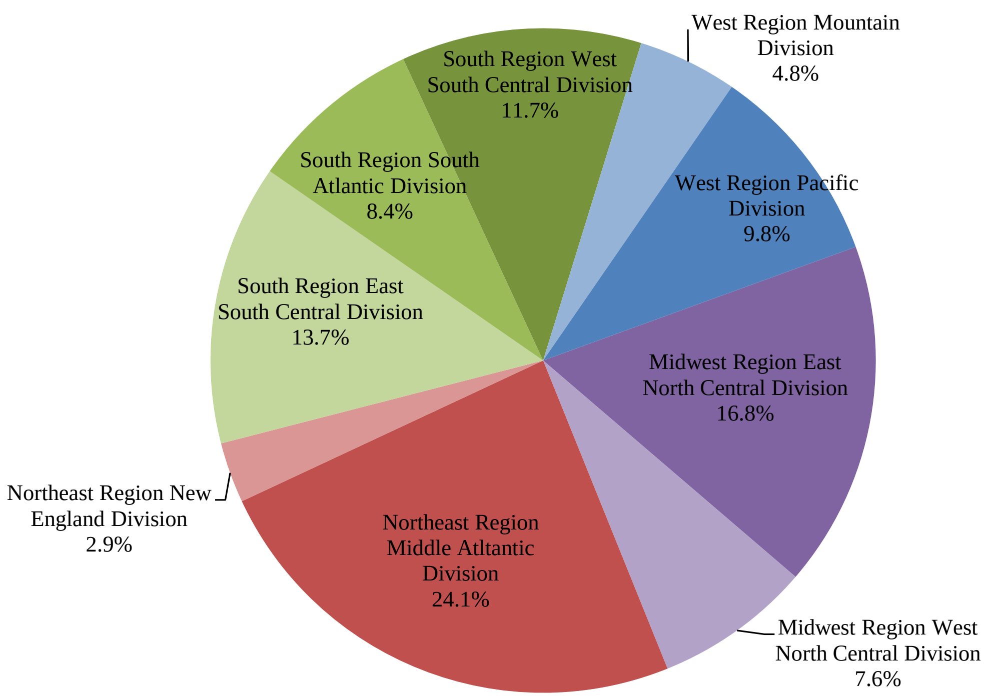


Figure 1.6: Real EDI Spending by Division ($ in millions)





Chapter 2: Do Economic Development Incentives Crowd Out Public Expenditures in U.S. States?

2.1 Introduction

"Economic development incentives waste a lot of money on a microscopic fraction of employees and states should focus on investing in infrastructure and education that benefit everyone, rather than showering big companies with dollars."— Greg LeRoy[12]

Economic development incentives, including tax and nontax instrument, are prominent in the state and local fiscal landscape in the United States. According to the New York Times, state and local governments offer more than $80 billion in incentives each year. Recipients come from a variety of industries: oil and gas, technology, entertainment, financial services and retailers. More than $1 million worth of incentives has been award to some 5,000 companies. Notably, these incentive offers account for a substantial portion of the overall spending in many communities.

The worry that economic development incentives may crowd out resources for productive public goods such as education and infrastructure is not new (Bartik, 1994; Rolnick and Burstein, 1995; Wilson, 1999; Gorin, 2008; Kenyon, Langley, and Paquin, 2012). In 2011, states reduced public goods provision and increased taxes by an aggregate of $156 billion according to the Center on Budget and Policy Priorities. Despite an extensive literature on economic development incentives, however, few studies focus on this aspect. Two notable exceptions are Greenstone and Moretti (2003) and Patrick (2012), both of which examine the effects on county finances following the

[12] Greg LeRoy, head of Good Jobs First, an economic development watchdog group, who was concerned about extensive offers of incentives to companies. "Sweet land of subsidy": http://www.economist.com/news/united-states/21576669-downturn-has-forced-states-be-savvier-and-more-careful-about-providing-tax.

opening of a large plant ("Million Dollar Plant"). This paper extends the literature by examining the effect of economic development incentives on the provision of public goods at the state level.

This paper contributes to existing literature in a number of important ways. First, given the widespread use of economic development incentives, it is of paramount importance that policymakers have a better understanding of the costs of such policies. The opportunity costs in terms of forgone public goods and services have been demonstrated to be critical for a state's economic growth (Helms, 1985; Mofidi and Stone, 1990; Fisher, 1997). Second, this study is aggregated at the state level. Previous literature has pointed out that the fiscal impacts of incentives at the state level are likely to be different from those at the local level (Peters and Fisher, 2004). Hence, it is important to examine state level tax incentives because they account for the biggest portion since the Tax Reform Act of 1986 (Luger and Bae, 2005). Third, by exploiting a new and exciting national database on incentives, I am able to explore the aforementioned question using panel data across U.S. states. My research, therefore, provides more generalizable results in contrast to previous literature which focuses on evaluating particular incentives or incentive programs in a single geographic area.

This paper empirically examines the relationship between incentives use and public expenditures using panel data for U.S. states from 1984 to 2008. The Arellano and Bond (1991) GMM approach is used to account for dynamic features associated with public expenditures. I also use forward orthogonal deviation to transform the data for GMM estimation to mitigate the problem of magnified gaps in an unbalanced panel associated with traditional first-differenced GMM estimator. Additionally, the empirical model includes lags of incentives to account for lagged effects of incentives expenditures.

The GMM estimation results indicate little effect of economic development incentives on most public goods in the first two time periods (including the current year), with negative repercussions appearing in year two. A dollar increase in incentives spending is associated with a $0.186 decrease in overall public expenditures two years later. There is also evidence of decreases in expenditures on some categorized productive public goods. At the same time, however, incentives are associated with increases in higher education expenditures. Overall, results of this paper lend support to the concern that economic development incentives crowd out spending on public goods and services. Considering the critical role that productive public goods and services play in promoting state economic growth, these results serve as additional warning for policymakers who contemplate using economic development incentives to stimulate economic growth.

The paper proceeds as follows. Section 2 surveys previous literature. Section 3 describes the state level panel data used for the estimation, while Section 4 presents the econometric models which will be used to investigate the effect of incentives expenditures. Section 5 presents an analysis of empirical results. Robustness checks are performed in Section 6, and Section 7 concludes.

2.2 Status of Literature

There is extensive literature examining the efficacy of economic development incentives in attracting business investments, creating jobs and stimulating economic growth. However, no consensus has been reached regarding the effectiveness of such policies (Patrick, 2014). Advocates of incentives see them as an effective means for growth and claim that incentives can "pay for themselves". They argue that business decisions will be influenced by incentives, leading to job creation and growth (Greenstone and Moretti, 2003). As a result, revenues from new economic activities negate the offered incentives. They also argue that the costs of incentives will be effectively lower if job creation reduces state's spending on welfare programs. Critics, however, believe that incentives are not effective at the margin, hence there is little growth induced, if any (Peters and Fisher, 2004). In addition, even if higher levels of economic activity are achieved, population growth may ensue. The additional strain on crowded public goods like infrastructure, education and other services are likely to prevent the expected growth from happening (Bartik, 1991). Taken as a whole, the literature is not very useful for policymakers in determining, under which circumstance, if any, to offer economic development incentives.

The lack of consensus in existing literature is attributable to differences in data and methodologies. This can be seen most prominently in case studies (Bartik and Erickcek, 2012; Weiner, 2009; Calcagno and Hefner, 2009; Wong and Stiles, 2007; Hoyt, Jepsen and Troske, 2007; Luger and Bae, 2005; Goodman, 2003). The myriad of case studies, however, suffer from lack of generalizability. Such case studies do not inform the use of economic development incentives elsewhere due to idiosyncratic nature of programs, industries, and location specific factors.

Existing state level studies generally find that incentives are positively correlated with state income and job growth (OhUallachain and Satterthwaite, 1992; De Bartolome and Spiegel, 1997; Goss and Phillips, 1997). However, results based on indirect measures of incentives in earlier research may not be very meaningful (Fisher and Peters, 1997).

More recent research exploits more detailed data and more advanced econometrics techniques. Greenstone and Moretti (2003) and Patrick (2012) are prime examples. The former examines the effect of winning a large plant on wages, property values, and public finances by using runner-up counties (i.e., the 'losers') as a counterfactual for winners. They do not find any reduction in public goods provision as a result of winning the bid. Patrick (2012) uses a matching strategy to identify the effect on employment, earnings as well as the fiscal impacts of a million dollar plant openings. She finds that winning counties appear to provide an increased level of public services to their growing populations, but that service improvements are funded by borrowing rather than the creation of a fiscal surplus.

The previous literature largely neglects the issue of how economic development incentives affect the provision of public goods and services. To my best knowledge, no study has explored the question at the state level. This question is important in that if incentives are not effective in influencing business location decisions, then using them would detract from growth by reducing funds available for spending on productive public goods and services.

Bartik (1991), Fisher (1997), and Wasylenko (1997) among others have reviewed how state and local fiscal policy in general affects growth.[13] Using a budget constraint approach, Helms' (1985) seminal paper establishes that economic growth is enhanced if increased revenue through higher taxes is used to fund public goods and

[13] Fisher (1997) concluded that at least "some public services clearly have a positive effect on some measures of economic development in some cases."

services such as education, highways, and public health and safety; while economic growth is retarded if revenue is used to finance transfer payments. The explanation is that benefits from improved public goods and services outweigh the disincentive effects of the associated higher taxes. His findings underscore the importance of considering impacts of a state's expenditures as well as by its taxes. Following Helms (1985), Mofidi and Stone (1990) reach similar findings regarding the effect on investment and manufacturing employment. They suggest that there are tradeoffs in state and local tax and expenditure policies and point out that raising transfer payment at cost of less public investments in education, health, highways and other public infrastructure has adverse consequences.

2.3 Data

2.3.1 Measures of Economic Development Incentives

Existing literature establishes that ideal measures for EDI do not exist (Fisher and Peters, 1997; Patrick, 2014). Many earlier studies use problematic data or use measures that inadequately reflect how active governments were in offering incentives. Simple counts of incentives programs, for example, can be severely misleading and are a poor measure of a state's economic development efforts. Programs on a state's book may be outdated and states may combine or divide programs without changing the generosity of incentives offered (Fisher and Peters, 1997). A state's economic development agency spending is also flawed because development agency funds can be used for noneconomic activities and EDI spending may not come from alternative sources.[14] Conclusions based on a measure like this are suspectful.

This paper exploits the Subsidy Tracker, gathered by the non-profit, non-partisan group Good Jobs First, as discussed in the literature (Jansa and Gray, 2014).[15] This database brings together public records of incentives granted to businesses under a wide variety of state programs and is publicly available online. It includes the actual dollar value of incentives granted, providing a measure of state economic development incentives spending that was previously elusive.

Subsidy Tracker is the first national search engine for EDI. It includes 12 broad categories of both tax and non-tax incentive programs (tax credits/rebates, property tax abatements, megadeal, grants/low-cost loans, enterprise zones, tax increment financing, training reimbursements, cost reimbursements, infrastructure assistance, industrial revenue bonds, tax credits/rebates and grants, tax credits/rebates and property tax abatements).[16] Despite extensive efforts to collect data, this database is unlikely to be inclusive of all incentive programs and the granted values, as discussed in the literature (Kenyon, Langley, and Paquin, 2012). Still, it is the most comprehensive database of incentives available.[17]

[14] Gorin (2008) provides an excellent example from Oklahoma. Notably, the data source for state economic development agency expenditure, i.e. the website for the National Association of State Development Agencies (NASDA), does not exist anymore.

[15] Subsidy Tracker database: http://www.goodjobsfirst.org/subsidy-tracker. For detailed description of incentives types included, please refer to Subsidy Tracker user guide: http://www.goodjobsfirst.org/subsidy-tracker-user-guide.

[16] Most incentive programs, however, are concentrated in two categories: tax credits/rebates and grants/low-cost loans. Hence, it is not feasible to estimate the model for each category of incentives.

[17] Harpel (2014) has a detailed discussion about Subsidy Tracker. http://www.smartincentives.org/blogs/blog/14754093-good-jobs-first-and-subsidy-tracker-2-0.

Each Subsidy Tracker database entry represents a subsidy granted to an individual firm within a specific state.[18] Due to limited data availability of government finance data, only entries up to 2008 are included. Subsidy values are aggregated by state-year.

2.3.2 Other Variables

Following Case, Hines and Rosen (1993), the dependent variables are the sum of state and local government expenditures in different categories.[19] The model is estimated using US data from 1984 to 2008. State and local government finance data were provided by the Census. All dollar values are expressed in terms of per capita and converted to real values (using 1982—1984 as the base year). Population density, the proportion of population under age 15, and the proportion of population above age 65 are from US Census. Bureau of Economic Analysis (BEA) provides data on personal income as well as Consumer Price Index (CPI). Financial data was matched with demographic information. In addition to overall public expenditures, this study focuses on spending on different categories of public goods and services including administration, corrections, education, health and human services, highways, police and fire protection, sanitation and utilities.[20]

Table 2.1 displays summary statistics. The dataset contains 378 observations. The descriptive statistics indicate considerable variation in expenditures on economic development incentives and spending on different categories of public goods and services across states. A closer examination of my sample reveals that Alaska in 1990

[18] I downloaded the version updated on Sept.10, 2013. Entries were aggregated by state-year.
[19] Case, Hines and Rosen (1993) argue that state government expenditures are more likely to reflect variation in the cross section assignment of spending responsibilities between state and local governments.
[20] Following Case, Hines and Rosen (1993), expenditures on health and human services are the sum of health and hospital spending and public welfare expenditures.

spent the most on incentives, about $653 per capita; while Virginia in 1991 spent the least on incentives, about $0.01 per capita. Of the average annual total state and local expenditures of $3,748.86 per capita, about 20 percent is spent on elementary education ($759.32), 20 percent on health and human services ($774.55), 7 percent on highways ($246.78), 6 percent on utilities ($209.82), and 4 percent on police and fire protection ($157.37).

Following Case, Hines and Rosen (1993) and Redoano (2007) among others, expenditures in various categories of public goods are regressed on a set of control variables, which will be discussed in detail in Section 4. In addition, up to three lags of incentives expenditures have also been added on the right hand sided to take into account of possible delayed effect, which restricts the sample to 27 or 28 states.

2.4 Regression Model

2.4.1 Baseline Model

Following the spirit of Case, Hines and Rosen (1993), the baseline model with all variables in levels is specified as follows:

(1) $$y_{it} = \beta_0 + \beta_1 I_{it} + \beta_2 x_{it} + \delta_i + \mu_t + \nu_{it},$$

where y_{it} is a category of public expenditures for state i in year t, I_{it} is incentives expenditures, and x_{it} is own state characteristics. The conditioning variables (x_{it}) include intergovernmental transfers (i.e. federal grant or federal intergovernmental revenue), state personal income, population density, and percentage of young and elder population. Grants and income measure resources available to state and local governments, while population density captures economies or diseconomies of scale in public goods provision. Demographic characteristics are included to account for the demand for public goods from specific demographic groups. State and year fixed effects are included to control for unobserved factors that do not change over time and macro shocks that affect all states in the same time period.

2.4.2 Dynamic Panel – GMM Estimation

Public expenditures, like many other economic variables, are dynamic in nature: spending decision are likely to follow historical patterns and are influenced by contemporaneous factors. Following Kelejian and Robinson (1993) and Redoano (2007), I include a one year lag of dependent variables in baseline model (1) in order to accommodate the sluggish adjustments in public expenditures over time. Expenditures on public goods and services for state i in year t are then modeled as follows:

(2) $$y_{it} = \beta_0 + \beta_1 y_{it-1} + \beta_2 I_{it} + \beta_3 x_{it} + \delta_{i} + \mu_t + \nu_{it},$$

Introducing lagged dependent variables, however, brings estimation challenges as illustrated below. To address these concerns, I use the Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond (1991). First, the GMM estimator gets rid of state fixed effects through differencing. Second, lagged endogenous variables in the level form and lagged exogenous variables in the differenced form serve as instruments. At last, specification tests are performed to check the validity of instruments. A problem with first differencing the model is that it magnifies gaps in data for an unbalanced panel. To mitigate the problem, I adopt forward orthogonal deviation to transform my data instead of using first differencing (Roodman, 2009).

2.4.2.1 Estimation Concerns

To see estimation challenges in a dynamic panel as laid out in (2), the model is written in a more generic form below:

(3) $y_{it} = \alpha y_{it-1} + \beta' x_{it} + \varepsilon_{it}$,

$\varepsilon_{it} = \delta_i + \mu_t + \nu_{it}$, for i = 1, 2, …,N, t = 2,…,T.

We can easily tell that lagged dependent variable y_{it-1} is correlated with δ_i in the error term. This endogeneity causes OLS estimator to be biased and inconsistent. Further, this problem cannot be circumvented with 2SLS or panel fixed effects estimator (Roodman, 2009). The Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond (1991) is a standard way to address these concerns (Roine et al, 2009).

2.4.2.2 First-Differenced GMM: Arellano and Bond (1991)

The GMM estimator starts with first differencing the model to remove state fixed effects. The transformed model is estimated using lagged levels of the dependent variable and endogenous variables, as well as differences of exogenous variables as instruments. The first differenced model and moment conditions are listed as below.

(4) $\Delta y_{it} = \alpha \Delta y_{it-1} + \beta' \Delta x_{it} + \Delta\varepsilon_{it}$,

$\Delta\varepsilon_{it} = (\delta_i - \delta_i) + \Delta\mu_t + \Delta\nu_{it}$, for i = 1, 2,…, N and t = 2,…,T ,

(5) E ($y_{it-s} \Delta\varepsilon_{it}$) = 0 for t = 3,4,…,T and s > = 2.

(6) E ($\Delta x_{it-s} \Delta\varepsilon_{it}$) = 0 for t = 3,4,…,T and s > = 2.

2.4.2.3 Forward Orthogonal Deviation Transformation – Adapted to an Unbalanced Panel

First differencing, however, shrinks the data set and amplifies gaps in an unbalanced panel. If y_{it} is missing, for example, then both Δy_{it} and Δy_{it+1} are missing in the first differenced transformed data. Alternative transformations, forward orthogonal deviations or orthogonal deviations, helps to mitigate the problem (Arellano and Bover 1995). In contrast to the first differencing transformation, which deducts observation from last period from the present one, the forward orthogonal deviation transformation subtracts the average of all future values from the present one (Roodman, 2009). Thus, the forward orthogonal deviation transformation only discards the last observation for each group, which minimizes data loss.[21]

Further, lagged observations are valid instruments since they do not enter the formula. A recent simulation study by Hayakawa (2009) shows that the GMM estimator transformed by forward orthogonal deviation tends to work better than the one transformed by first differencing. Given that my panel is unbalanced with gaps, I adopt the forward orthogonal deviation transformation to preserve observations. [22]

2.4.2.4 Specification Tests for GMM Estimators: AR (1), AR (2) and Sargan Tests

The consistency of the difference GMM estimator depends critically on the validity of the moment conditions listed in (5) – (6) and the lack of second order serial correlation in the error terms. The Sargan/Hansen test is used to examine the validity of instruments. The null hypothesis is that the instruments are exogenous as a group. As a result, a higher p-value of the Sargan/Hansen statistic is preferred.

The other important diagnostic is the AR test for autocorrelation of the residuals. The consistency of the GMM estimator relies on the lack of second order serial correlation. By construction, the residuals of the first differenced equation should possess serial correlation. Accordingly, the null is always rejected for the AR (1) test. For instruments to be valid, differenced residuals should not show significant second order of serial correlation. Accordingly, a high reported p-value in AR (2) test indicates

[21]Further, Hayakawa (2009) shows in a recent simulation study that the GMM estimator transformed by forward orthogonal deviation tends to perform better than the one transformed by first differencing.
[22] Please refer to Roodman (2009) for mathematical representation.

that the moment conditions are valid. If the AR (2) statistic is significant, longer lags need to be used.

2.4.3 Capturing Lagged Effects of Incentives

Lastly, I include lagged values of incentives expenditures to capture possible delayed effects of incentives to allow time for reactions to occur. Specifically, the dynamic panel model in (2) is modified as follows:

(7) $y_{it} = \beta_0 + \beta_1 y_{it-1} + \beta_2 I_{it} + \beta_3 I_{it-s} + \beta_4 x_{it} + \delta_i + \mu_t + \nu_{it}$, where s =1, 2, or 3.

2.5 Results

Regression results of equation (7) are summarized in Table 2.2 with each column representing a specific category of public goods. OLS, FE and Difference GMM estimation methods have been performed. As discussed in the literature (Roodman, 2009), the lagged dependent variable was positively correlated with the error, which biases β_1, the coefficient associated with Y_{it-1}, upward for OLS estimation; whereas the estimate of β_1 is biased downward due to the negative sign in front of the within group transformed error from the fixed effects regression. Therefore, a reliable estimate should lie in between the two values, which serves a useful check.[23]

Coefficient estimates are generated using a one-step GMM.[24] The second lag or more of endogenous variables (lagged public expenditures, y_{it-1}) are selected as instruments while all lags for exogenous variables (grants, personal income, incentives, population density and percentages of old as well as young population) serve as

[23] This condition is met with my results, but due to space limitation, Only GMM results are presented here. OLS and FE results are available upon request.
[24] For applied work using the one-step GMM estimator, please refer to Arai, Kinnwall, and Thoursie (2004), Falk (2006), Huang, Hwang, and Yang (2008), and Yao (2006).etc.

instruments. Sargan test statistics are presented to examine the validity of the instruments. The reported AR (1), AR (2) and Sargan results support the validity of selected instruments in most cases.

In general, the results indicate that incentives expenditures are not contemporaneously correlated with public expenditures at the state level. They are, however, negatively correlated with overall expenditures after two years, and the relationship is statistically significant at conventional levels. There is also evidence of decreases in expenditures on corrections, elementary education, health and human services, police and fire protection, sanitation and utilities associated with incentives expenditures. Spending on higher education, on the other hand, is found to be positively associated with incentives expenditures. It is worth noting that most of the decreases in spending do not occur until two years later, which seems to indicate that at least in the very short run incentives do not contribute to spending on public goods and services. The coefficients associated with incentives spending are not only statistically significant, but also have potentially huge economic effects.

For the average state, one dollar increase in incentives is correlated with $0.186 decrease in direct expenditures two years later. Given that the average state spends 20.2 dollars per capita on incentives during sample period, this implies a 3.76 (20.2*0.186) dollars decrease in per capita direct expenditures, about 0.1% of direct expenditures two years later. As an example of New Mexico in 2004 which had the highest incentives expenditures, 557.74 dollars of incentives spending would be associated with 103.74 dollars less in per capita spending two years later, accounting for about 2.5% of direct expenditures in 2006 (103.74/4105.73*100=2.5%).

Take health and human services as another example. A dollar increase in per capita incentives is associated with 16 cents decrease in per capita spending on health and human services two years later. Given that the average state spends 20.2 dollars per capita on incentives during the sample period, this implies a $3.23 (20.2*0.16) drop in per capita health and human services expenditures two years later, about 0.2% of average health and human spending (3.23/774.5*100=0.4%). For New Mexico in 2004, 557.74 dollars of incentives is associated with 89.24 dollars less per capita spending two years later, which is about 10% of its spending on health and human services in 2006 (89.24/893*100=10%).

Regarding other control variables, grants are generally positively and significantly correlated with expenditures on different categories of public goods and services. The estimated coefficient on grants for direct expenditures in GMM estimation indicate that for a dollar increase in federal grants, states spend about half of it, the magnitude of which is in sharp contrast with that of state personal income. The phenomenon that state and local governments spend much more out of their grant income than personal income of their residents is called flypaper effect. My estimate of this "flypaper effect" is comparable to previous estimates, which range from as small as 0.25 to around unity with most estimates around 0.5 (Hines and Thaler, 1995).

Demographic characteristics can influence the composition of public spending to the extent that they determine the needs and preferences of population for public goods. The inclusion of population density provides information about scale economies and potential congestion effects in the provision of public goods. The estimated coefficients for population density are either insignificant or positive. The latter indicates diseconomies of scale. My results are similar to those of Ermini and Santolini (2010) and Silva, Veiga, and Portela (2011). The proportion of population above 65 is mostly negatively associated with expenditures on public goods, consistent with previous studies (Case, Hines and Rosen, 1993; Redoano, 2007). The effect of the share of young population (under 15) varies with the category of public goods.

Baseline GMM estimation indicates that the share of young population is negatively associated with expenditures on higher education, sanitation and highways, while positively associated with health and human services expenditures. This makes sense as higher education expenditures are devoted to population aged 17 years or above. Additionally, younger people generally live with their parents. Hence a greater percentage of young population implies fewer households, which reduces spending on sanitation and utilities. Similar reasoning applies to highways expenditures: a higher percentage of young people implies fewer drivers on the road, and consequently less need to maintain/expand highways. A larger proportion of young people, however, can be expected to increase expenditures on health and hospitals as well as public welfare. The proportion of young people is also correlated with higher direct expenditures overall.

2.6 Robustness Checks[25]

A number of robustness checks have been performed. First, to test potential impact of outliers, I limit my sample to the time period after 1990 when data coverage

[25] I also estimated alternative model to investigate if the changes in incentives expenditures have an impact on changes in expenditures on public goods. The first differenced model, however, essentially looks at contemporaneous effects of incentives on the provision of public goods. It is, therefore, not surprising that most results are insignificant considering it takes time for incentives to have an impact.

on incentives is more comprehensive. I then perform the same GMM estimation as before. Results are presented in Table 2.3.

Coefficient estimates are qualitatively the same as in the previous estimation (Table 2.2). The coefficient on one year lag of public expenditure variables remains positive and significant at conventional levels. Total grants are positively associated with public expenditures when significant. Incentives coefficients estimates are qualitatively similar to that of baseline estimation but the magnitude becomes smaller for direct expenditures, which decreases from 0.186 to 0.146. Estimated coefficients on administration and highways expenditures remain insignificant. Regarding corrections estimates, incentives are only associated with decreases in expenditure three years later. The magnitude of the estimated impact on elementary education also becomes bigger, from 0.065 to 0.071. Incentives continue to be positively associated with expenditures on higher education but are of smaller magnitudes. Expenditures on police and fire, sanitation, utilities are still negatively associated with incentives expenditures; however, estimated coefficients are smaller. Overall, the results are qualitatively similar except that estimated coefficients on incentives are smaller using the limited sample.

Additionally, the basic model is estimated through difference GMM (DGMM) where incentives are treated as endogenous. Because the extent to which states use incentives might depend on other unobservable factors which influence spending choices, the incentives variable I_{it} may be correlated with error term. To deal with this potential endogeneity problem, I instrument I_{it} with its lags. The results using instruments for I_{it} are presented in Table 2.4. Compared with the results in Table 2.2, the estimated negative correlation between incentives and expenditures on public good are strengthened in most cases: not only do the magnitudes become larger, the significant level also increases. The estimated coefficient on direct expenditures increases in magnitude to 0.193. For police and fire protection, health and human services, sanitation and utilities expenditures, estimated coefficients also become larger and the significance level increases to 5%. Overall, this suggests that the effects of incentives may be underestimated if potential endogeneity is ignored. Estimates on demographic variables are very similar to the baseline estimates except that the percentage of young population is also found to be negatively associated with administration spending: a one percentage increase in young population is associated with about 2.5 dollars decrease in per capita administration spending.

A potential problem with difference GMM estimator is that lagged independent variables can be poor instruments when they do not change much over time. This does not seem to be a problem for my estimation. Nevertheless, a third robustness estimates the baseline model through dynamic system GMM, developed by Blundell and Bond (1998). It helps to address the aforementioned problem with difference GMM by providing more moment conditions available from the level equation. Following Blundell and Bond (1998) the level equation (2) is incorporated in the first-differenced GMM. Variables in the level equation are instrumented with their own differences.

Table 2.5 reports system GMM regression results with the incentives expenditure variable treated as exogenous. The results are basically consistent with the baseline estimates in Table 2.3, where the incentives variable is treated the same way. The only major difference is that the estimated coefficient on direct expenditures is much larger, almost doubling from previous estimate, reaching -0.334. And one year lag of incentives now is negatively associated with expenditures on highways. Demographic variables are similar to previous estimates. Table 2.6 presents the last robustness check, where I estimate the model using system GMM estimator with incentives being treated as endogenous. Again, the results are similar.

2.7 Conclusion

EDI are widely used by state and local governments as a tool to lure investment, create jobs and ultimately induce economic growth. Despite sizeable incentives offered, very few states are effective in evaluating the EDI programs offered (Pew Center Report, 2012). The prominence of business incentives in debates on public policy and economic development has led to extensive theoretical and empirical research. Most empirical research to date, however, has focused on evaluating the employment and investment/growth effects of a particular incentive program in a single geographic area.

This paper takes a novel approach by investigating whether incentive spending crowds out spending on other public goods and services at the state level. With the benefit of a national database of economic development incentives, dynamic panel data analysis is implemented. Estimates using a GMM estimator controlling for the dynamic nature of state spending as well as possible lagged effects of incentives show that public expenditures are negatively associated with incentive use. In particular, the main findings indicate that incentives expenditures are associated with decreases in expenditures on productive public goods such as education, health and human services, sanitation and utilities. Empirical evidence shows that incentives do not seem to contribute to more spending on productive public goods and services after two years. This contradicts the claims that incentives lead to beneficial growth in the economy. Or if growth occurs, it does not lead to expansion of spending on productive public goods and services.

It is worth noting that Subsidy Tracker database has limitations; nonetheless, it is an improved measure for incentives compared with previous studies and it is the best data publicly available to data. In times of fiscal stress, it is of paramount importance to understand what states are giving up especially given the close link between public services and economic growth (Helms, 1985; Mofidi and Stone, 1990; Miller and Russek, 1997). My findings echo the long standing criticism against incentives spending (Rolnick and Burstein, 1995; Fisher and Peters, 2004). For policymakers who care about long term economic growth, the extensive use of incentives is questionable.

Table 2.1: Summary Statistics (# of observations=378)

Variables	Mean	Std. Dev.	Min	Max
Subsidy Spending ($)	20.20	55.49	0.01	652.70
Grants ($)	673.40	200.00	317.77	1,602.35
Income ($)	17,160.82	2,863.98	10,690.91	26,940.42
Population	6,648,663	6,690,211	547,160	36,600,000
Total State Area (sq.mi)	73,487.70	88,428.92	1,545.05	663,267.30
Population Density (total)	179.13	213.27	0.82	998.83
Under 15 (%)	20.77	1.60	17.02	28.03
Above 65 (%)	12.64	1.91	3.84	18.55
Expenditures:				
Direct Expenditures ($)	3,748.86	863.06	1,933.09	8,505.26
Administration ($)	155.04	55.01	72.17	502.27
Corrections ($)	91.78	30.56	24.71	174.18
Elementary Education ($)	759.32	163.88	370.67	1,339.45
Higher Education ($)	316.20	84.80	155.79	550.21
Health & Human Services ($)	774.55	201.40	335.71	1,558.95
Highways ($)	246.78	87.96	123.21	859.57
Police & Fire ($)	157.37	46.05	64.11	278.78
Sanitation ($)	92.32	27.69	34.86	175.14
Utilities ($)	209.82	143.27	39.58	1,035.49

Sources: Incentives data are from Subsidy Tracker database. Data on demographic characteristics are from Bureau of the Census. Personal Income data are drawn from Bureau of Economic Analysis, and the rest government finance data are from Census historical database.

Notes:

(1) All dollar figures have been converted to real values, deflated by CPI (1982-84=100).
(2) All dollar values are on a per capita basis.
(3) Population density is in persons per square mile.

Table 2.2: Baseline Difference GMM Results

	Direct_Exp	Admin	Corretions	Elem Edu	Higher Edu	Health & Human	Highways	Police & Fire	Sanitation	Utilities
Y(t-1)	0.833	0.921	0.690	0.822	0.800	0.822	0.438	0.770	0.671	0.325
	[0.094]***	[0.111]***	[0.059]***	[0.125]***	[0.073]***	[0.196]***	[0.135]***	[0.085]***	[0.105]***	[0.266]
Grants	0.520	0.005	-0.004	0.055	-0.003	0.193	0.161	0.007	-0.004	-0.044
	[0.118]***	[0.019]	[0.015]	[0.051]	[0.018]	[0.072]**	[0.055]***	[0.009]	[0.014]	[0.036]
Income	0.016	0.001	0.000	0.007	0.001	-0.005	0.002	-0.001	-0.001	-0.006
	[0.014]	[0.002]	[0.002]	[0.005]	[0.002]	[0.007]	[0.005]	[0.002]	[0.001]	[0.004]*
I(t)	-0.254	0.013	-0.076	0.009	0.047	-0.034	-0.059	-0.016	-0.003	-0.150
	[0.185]	[0.009]	[0.036]**	[0.021]	[0.022]**	[0.099]	[0.036]	[0.008]**	[0.020]	[0.099]
I(t-1)	0.053	0.017	-0.010	0.007	0.044	0.079	-0.016	-0.013	-0.013	-0.032
	[0.157]	[0.020]	[0.008]	[0.038]	[0.015]***	[0.088]	[0.035]	[0.009]	[0.009]	[0.034]
I(t-2)	-0.186	0.002	-0.022	-0.065	0.045	-0.160	0.036	-0.007	-0.029	-0.059
	[0.076]**	[0.007]	[0.009]**	[0.019]***	[0.024]*	[0.074]**	[0.037]	[0.014]	[0.012]**	[0.026]**
I(t-3)			-0.026							0.012
			[0.009]***							[0.069]
Pop_Density	2.872	0.281	0.020	0.711	-0.125	1.442	0.002	0.054	0.125	0.684
	[1.259]**	[0.079]***	[0.077]	[0.571]	[0.136]	[0.541]**	[0.409]	[0.068]	[0.106]	[0.448]
Under 15	20.241	-2.087	-1.192	4.801	-3.043	11.586	-10.585	-0.044	-3.425	-5.722
	[13.598]	[1.819]	[1.852]	[5.722]	[1.562]**	[6.432]*	[6.616]	[1.620]	[1.152]***	[4.003]
Above 65	-36.209	2.603	0.196	-3.365	5.447	7.947	-9.758	-4.129	2.746	8.957
	[21.057]*	[2.384]	[1.505]	[9.024]	[3.650]	[16.940]	[8.944]	[2.903]	[2.868]	[8.706]
AR(1)	0.001	0.011	0.038	0.026	0.015	0.037	0.041	0.002	0.006	0.037
AR(2)	0.177	0.158	0.101	0.223	0.226	0.454	0.785	0.947	0.715	0.200
Sargan Test	0.287	0.278	0.487	0.519	0.306	0.169	0.405	0.124	0.300	0.310

Notes:

(1) Column variables are categories of public expenditures for state and local government.

(2) All regressions include state and year fixed effects. Standard errors are in brackets, robust to heteroskedasticity and serial correlation.

(3) Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 2.3: Difference GMM (Restricted Sample Period 1991-2008)

	Direct_Exp	Admin	Corrections	Elem Edu	Higher Edu	Health & Human	Highways	Police & Fire	Sanitation	Utilities
Y(t-1)	0.920	0.921	0.630	0.879	0.830	0.810	0.470	0.869	0.535	0.088
	[0.094]***	[0.110]***	[0.069]***	[0.057]***	[0.056]***	[0.171]***	[0.129]***	[0.183]***	[0.131]***	[0.258]
Grants	0.474	0.006	-0.006	0.056	-0.006	0.191	0.141	0.007	0.002	-0.043
	[0.123]***	[0.016]	[0.017]	[0.045]	[0.015]	[0.070]**	[0.042]***	[0.012]	[0.014]	[0.036]
Income	0.018	0.001	0.000	0.007	0.000	-0.006	0.001	0.000	-0.002	-0.008
	[0.013]	[0.002]	[0.001]	[0.004]	[0.001]	[0.006]	[0.005]	[0.002]	[0.002]	[0.005]
I(t)	-0.054	0.013	0.010	0.004	0.025	-0.035	-0.058	-0.014	0.010	-0.032
	[0.100]	[0.009]	[0.020]	[0.020]	[0.014]*	[0.097]	[0.036]	[0.008]*	[0.013]	[0.059]
I(t-1)	0.126	0.016	0.000	0.001	0.035	0.078	-0.011	-0.011	-0.005	-0.023
	[0.146]	[0.020]	[0.008]	[0.037]	[0.017]**	[0.088]	[0.036]	[0.010]	[0.008]	[0.028]
I(t-2)	-0.146	0.002	-0.010	-0.071	0.036	-0.160	0.037	-0.006	-0.023	-0.054
	[0.059]**	[0.007]	[0.009]	[0.016]***	[0.025]	[0.073]**	[0.037]	[0.012]	[0.011]**	[0.028]*
I(t-3)			-0.028							0.003
			[0.008]***							[0.046]
Pop_Density	2.011	0.282	0.024	0.476	-0.123	1.462	0.018	0.004	0.240	1.007
	[1.253]	[0.079]***	[0.072]	[0.417]	[0.118]	[0.521]***	[0.383]	[0.097]	[0.218]	[0.556]*
Under 15	28.081	-2.048	-1.941	6.185	-2.197	11.155	-10.974	0.739	-4.763	-8.260
	[8.420]***	[1.681]	[1.571]	[4.525]	[1.539]	[5.158]**	[6.211]*	[1.803]	[1.655]***	[4.594]*
Above 65	-50.685	2.622	0.803	-6.435	3.952	8.788	-9.938	-4.918	5.420	10.409
	[30.504]	[2.375]	[1.574]	[7.776]	[3.237]	[15.853]	[8.352]	[2.609]*	[5.053]	[11.878]
AR(1)	0.002	0.011	0.033	0.005	0.012	0.038	0.045	0.009	0.013	0.043
AR(2)	0.074	0.159	0.113	0.121	0.246	0.458	0.745	0.818	0.586	0.348
Sargan Test	0.606	0.321	0.232	0.470	0.234	0.207	0.391	0.854	0.227	0.519

Notes:

(1) Column variables are categories of public expenditures for state and local government.
(2) All regressions include state and year fixed effects. Standard errors are in brackets, robust to heteroskedasticity and serial correlation.
(3) Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

2.4: Difference GMM Treating Incentives as Endogenous

	Direct_Exp	Admin	Corrections	Elem Edu	Higher Edu	Health & Human	Highways	Police & Fire	Sanitation	Utilities
Y(t-1)	0.810	0.822	0.669	0.778	0.839	0.775	0.550	0.649	0.678	0.333
	[0.069]***	[0.103]***	[0.051]***	[0.053]***	[0.069]***	[0.115]***	[0.118]***	[0.072]***	[0.085]***	[0.274]
Grants	0.541	0.006	-0.006	0.061	-0.004	0.197	0.132	0.016	0.001	-0.043
	[0.104]***	[0.021]	[0.016]	[0.042]	[0.016]	[0.063]***	[0.039]***	[0.011]	[0.011]	[0.035]
Income	0.014	0.001	0.000	0.008*	0.000	-0.007	0.001	-0.001	-0.001	-0.007
	[0.012]	[0.002]	[0.001]	[0.004]	[0.002]	[0.005]	[0.004]	[0.001]	[0.001]	[0.004]*
I(t)	-0.259	0.002	0.010	0.013	0.062	-0.073	-0.084	-0.019	-0.002	-0.141
	[0.177]	[0.010]	[0.019]	[0.022]	[0.035]*	[0.085]	[0.071]	[0.007]***	[0.019]	[0.099]
I(t-1)	0.036	0.012	-0.001	0.012	0.050	0.062	-0.013	-0.016	-0.012	-0.030
	[0.152]	[0.020]	[0.008]	[0.037]	[0.015]***	[0.076]	[0.024]	[0.010]	[0.009]	[0.033]
I(t-2)	-0.193	-0.002	-0.011	-0.060	0.049	-0.169	0.031	-0.009	-0.029	-0.058
	[0.077]**	[0.007]	[0.009]	[0.016]***	[0.027]*	[0.069]**	[0.046]	[0.014]	[0.012]**	[0.026]**
I(t-3)			-0.029							0.011
			[0.009]***							[0.069]
Pop_Density	3.039	0.352	0.037	0.895**	-0.105	1.510	0.016	0.124	0.189	0.705
	[1.111]***	[0.111]***	[0.066]	[0.414]	[0.124]	[0.415]***	[0.357]	[0.080]	[0.163]	[0.441]
Under 15	20.631	-2.537	-1.925	4.324	-2.429	11.073	-8.695	0.248	-3.606	-5.725
	[9.716]**	[1.982]	[1.562]	[4.933]	[1.775]	[4.704]**	[6.265]	[1.507]	[1.311]***	[3.835]
Above 65	-37.754	3.775	0.508	-0.908	4.610	10.505	-10.579	-3.838	4.435	7.879
	[19.499]*	[3.217]	[1.601]	[8.679]	[3.430]	[12.480]	[7.944]	[3.158]	[3.927]	[8.399]
AR(1)	0.001	0.006	0.028	0.006	0.014	0.018	0.037	0.005	0.004	0.042
AR(2)	0.103	0.17	0.108	0.019	0.253	0.477	0.736	0.853	0.675	0.202
Sargan Test	0.276	0.344	0.251	0.087	0.199	0.178	0.532	0.085	0.430	0.333

Notes:

(1) Column variables are categories of public expenditures for state and local government.
(2) All regressions include state and year fixed effects. Standard errors are in brackets, robust to heteroskedasticity and serial correlation.
(3) Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 2.5: System GMM Treating Incentives as Exogenous

	Direct_Exp	Admin	Corrections	Elem Edu	Higher Edu	Health & Human	Highways	Police & Fire	Sanitation	Utilities
Y(t-1)	1.173	0.992	0.973	0.968	1.008	1.000	0.926	1.039	0.954	0.962
	[0.179]***	[0.032]***	[0.025]***	[0.016]***	[0.026]***	[0.032]***	[0.031]***	[0.010]***	[0.067]***	[0.037]***
Grants	-0.253	-0.001	0.000	0.016	0.005	0.030	0.026	0.000	0.000	0.003
	[0.346]	[0.003]	[0.003]	[0.010]	[0.009]	[0.023]	[0.011]**	[0.002]	[0.003]	[0.011]
Income	-0.033	0.000	0.000	0.000	0.000	-0.002	0.000	0.000	0.000	0.000
	[0.033]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]***	[0.000]	[0.001]
I(t)	-0.237	0.003	0.024	0.008	0.006	-0.016	-0.076	-0.012	0.006	-0.023
	[0.187]	[0.008]	[0.014]	[0.010]	[0.011]	[0.038]	[0.025]***	[0.010]	[0.009]	[0.036]
I(t-1)	-0.342	-0.001	0.009	-0.006	0.022	0.051	0.019	-0.009	-0.011	-0.023
	[0.427]	[0.009]	[0.005]*	[0.016]	[0.008]**	[0.061]	[0.016]	[0.004]**	[0.005]**	[0.013]*
I(t-2)	-0.344	-0.004	-0.005	-0.072	0.017	-0.154	0.036	-0.002	-0.026	0.027
	[0.168]**	[0.004]	[0.005]	[0.014]***	[0.022]	[0.041]***	[0.031]	[0.008]	[0.010]***	[0.065]
I(t-3)			-0.023							
			[0.006]***							
Pop_Density	0.103	0.001	-0.003	0.031	-0.002	0.025	-0.012	0.000	0.003	0.002
	[0.077]	[0.003]	[0.002]	[0.011]***	[0.004]	[0.014]*	[0.007]	[0.001]	[0.005]	[0.009]
Under 15	-15.436	-0.330	-0.518	-3.585	-1.411	0.631	0.120	-0.089	-0.457	0.035
	[14.865]	[0.003]	[0.289]*	[1.777]**	[0.841]	[2.549]	[1.154]	[0.390]	[0.390]	[1.248]
Above 65	-1.810	-0.185	-0.635	-2.231	-0.686	0.157	0.082	-0.205	0.084	-0.011
	[7.908]	[0.568]	[0.185]***	[0.814]***	[0.473]	[1.787]	[0.574]	[0.217]	[0.308]	[0.889]
AR(1)	0.002	0.009	0.033	0.009	0.024	0.019	0.034	0.005	0.001	0.034
AR(2)	0.179	0.171	0.101	0.020	0.267	0.496	0.732	0.745	0.716	0.170
Sargan Test	0.565	0.182	0.529	0.345	0.207	0.173	0.493	0.434	0.585	0.791

Notes:

(1) Column variables are categories of public expenditures for state and local government. Constant is omitted from the table.
(2) All regressions include state and year fixed effects. Standard errors are in brackets, robust to heteroskedasticity and serial correlation.
(3) Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table 2.6: System GMM Treating Incentives as Endogenous

	Direct_Exp	Admin	Corrections	Elem Edu	Higher Edu	Health & Human	Highways	Police & Fire	Sanitation	Utilities
Y(t-1)	0.996	0.997	0.963	0.969	1.021	1.050	0.924	1.018	0.975	1.009
	[0.059]***	[0.024]***	[0.020]***	[0.018]***	[0.017]***	[0.034]***	[0.023]***	[0.010]***	[0.015]***	[0.009]***
Grants	0.193	0.005	0.000	0.023	-0.001	0.000	0.022	0.000	0.002	0.005
	[0.121]	[0.004]	[0.003]	[0.011]**	[0.008]	[0.018]	[0.012]*	[0.003]	[0.003]	[0.005]
Income	-0.007	0.000	0.000	0.000	0.001	-0.003	-0.001	0.000	0.000	-0.001
	[0.013]	[0.000]	[0.000]	[0.001]	[0.000]*	[0.002]	[0.001]	[0.000]**	[0.000]	[0.000]
I(t)	-1.493	-0.032	-0.016	-0.093	0.065	0.014	-0.097	-0.035	0.008	-0.022
	[0.982]	[0.036]	[0.020]	[0.077]	[0.030]**	[0.084]	[0.077]	[0.015]**	[0.007]	[0.037]
I(t-1)	-0.056	-0.007	0.013	-0.007	0.017	0.046	0.027	-0.006	-0.014	-0.033
	[0.161]	[0.010]	[0.005]**	[0.024]	[0.008]**	[0.060]	[0.018]	[0.006]	[0.004]***	[0.011]***
I(t-2)	-0.339	-0.008	-0.003	-0.081	0.020	-0.167	0.038	-0.006	-0.027	0.021
	[0.117]***	[0.006]	[0.005]	[0.018]***	[0.025]	[0.033]***	[0.027]	[0.008]	[0.008]***	[0.050]
I(t-3)			-0.016							
			[0.006]**							
Pop_Density	0.110	0.001	-0.001	0.034	-0.002	0.025	-0.011	0.002	0.002	0.007
	[0.053]**	[0.004]	[0.002]	[0.011]***	[0.004]	[0.013]*	[0.007]	[0.001]	[0.003]	[0.006]
Under 15	-0.864	0.018	-0.705	-3.208	-1.356	0.423	-0.196	0.124	-0.475	-0.224
	[9.325]	[0.004]	[0.308]**	[1.906]	[0.995]	[2.450]	[1.030]	[0.515]	[0.432]	[0.638]
Above 65	-6.384	-0.223	-0.755	-2.565	-0.466	0.209	-0.048	-0.194	0.111	0.196
	[4.914]	[0.630]	[0.204]***	[0.819]***	[0.526]	[1.758]	[0.499]	[0.257]	[0.295]	[0.389]
AR(1)	0.002	0.012	0.033	0.011	0.028	0.022	0.034	0.006	0.000	0.031
AR(2)	0.269	0.167	0.107	0.117	0.243	0.490	0.721	0.993	0.502	0.161
Sargan Test	0.640	0.226	0.709	0.132	0.707	0.185	0.884	0.185	0.219	0.380

Notes:

(1) Column variables are categories of public expenditures for state and local government. Constant is omitted from the table.

(2) All regressions include state and year fixed effects.Standard errors are in brackets, robust to heteroskedasticity and serial correlation.

(3) Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) level.

Chapter 3: Strategic Interaction and Economic Development Incentives Policy: Evidence from U.S. States

3.1 Introduction

State and local governments spend billions of dollars each year on economic development incentives (EDI), often in an attempt to attract or retain investment, create jobs and ultimately stimulate growth. According to New York Times, Texas offers the most incentives, exceeding 19 billion dollars a year, while Alaska, West Virginia and Nebraska award the most in terms of per capita. Despite of the extensive body of research on EDI, no consensus has been reached about the efficacy of such policies (Peters and Fisher, 2004; Patrick, 2014). Both proponents and opponents of EDI programs have offered theoretical, empirical, and/or case study evidence to support their claims.

A related but much smaller literature examines factors motivating communities to engage in offering economic development incentives. Economic, political and demographic characteristics have been examined as determinants (Felix and Hines, 2013). Important as these factors are, my paper highlights another determinant of EDI spending at the state level: the EDI spending of neighboring states.

Anecdotal evidence suggests that EDI expenditure within one state does affect that of another. For example, a few months after Kansas recruited AMC Entertainment, which moved barely across the border from Missouri, with a $36 million award, Missouri attracted Applebee's headquarters from Kansas.[26] Border wars like these are

[26] As Companies Seek Tax Deals, Governments Pay High Price: http://www.nytimes.com/2012/12/02/us/how-local-taxpayers-bankroll-corporations.html

not limited to the middle part of the country.[27] The creation of the Texas Enterprise Fund (TEF), the largest discretionary fund to entice companies to relocate, has inspired all of Texas' neighbors to imitate. Such interstate competition has become a rule rather than exception. As a result, every state nowadays has at least one type of incentives programs (Truitt, 2004; Pew Center Study, 2012).

This rivalry among states has been extensively discussed in academia (Ellis and Rogers, 2000; Patrick, 2014). Some believe that the use of incentives targeted as specific businesses induces a loss to the overall economy at the national level and hence have called for the Congress to take action to "end the economic war among states" (Rolnick and Burstein, 1995). Others have worried about whether such competition simply leads to a reshuffling of business locations and under-provision of public goods (Bartik, 1991; Fish and Peters, 1997; Gorin, 2008; Wang, 2015). Surprisingly, there is little empirical research to substantiate the existence and the extent of policy interaction in incentives competition.

Although public economics has long incorporated strategic interaction in theoretical modelling (Brueckner, 2003), most empirical research focuses on communities' own characteristics in analyzing EDI activities. Man (1999) and Byrne (2005) are the only researchers explicitly accounting for policy interaction in the study of communities' decision to adopt tax increment financing (TIF), a specific type of economic development incentives. The aforementioned anecdotal evidence suggests that EDI competition is also relevant at the state level. A more realistic and natural model of the decision making process therefore considers influence of EDI spending

[27] Tax battle in the Northeast (New York versus New Jersey): http://www.nytimes.com/video/business/100000001936106/tax-battle-in-the-northeast.html

decision of neighboring states. This paper examines EDI spending at the state level and accounts for strategic interaction using spatial econometrics technique.

It extends existing literature in a number of ways. With the benefit a national search engine for EDI, I verify the existence and estimate the extent of EDI policy interaction in incentives expenditures at the state level. In addition, panel data across states allows for a more generalizable analysis compared with prior research that focuses on a specific geographic area and/or a specific type of incentive programs. Further, it extends Byrne's (2005) spatial econometrics framework by incorporating both state and year dummies to mitigate concerns associated with potential omitted variables bias. This paper further contributes to the literature by shedding light on whether or not interstate EDI competition is more intense after the 2008 financial crisis and if political cycle plays a role in EDI competition.

Using a sample across 22 U.S. states, I find that states appear to choose their EDI spending levels strategically during the period 2000-2011. More specifically, states respond positively to EDI spending level set in their neighbors: EDI spending increases in neighboring states are matched by higher EDI spending in the home state. The magnitudes of response cluster around 56 to 60 cents for each dollar's increase depending on the definition of neighbors. Additional evidence suggests that the EDI competition has not become more intense after the most recent financial crisis states, nor is election cycle the driving force of EDI competition. The overall results indicate that EDI are used as a way to compete for capital and jobs against neighboring states, most close in nature to tax competition. This paper contributes to the heated debate over incentives use and helps to better understand the nature of spillovers regarding EDI use.

Results of this paper provide valuable guidance to policymakers. The remainder of the paper proceeds as follows. Section II provides a brief overview of existing literature. Section III introduces the empirical model and estimation challenges. The data are described in Section IV. Section V presents empirical findings. Robustness checks and extensions are discussed in Section VI, and. Section VII concludes.

3.2 Overview of Prior Research

Fiscal policy interdependence has long interested researchers (Brueckner, 2003; Revelli, 2005). Several channels contribute to the observed policy interdependence. Jurisdictions may compete against each other for mobile resources, hence setting policy variables interdependently or strategically, as highlighted in the extensive literature on "tax competition" and "welfare competition". The former is attributable to the fact that local governments compete for mobile resources (e.g. capital) through taxation. Their tax base, therefore, is affected by both their own and their neighbors' tax rates. To avoid pushing away taxpayers, communities set their tax rates strategically. Evidence of this mechanism is well documented in the literature (Wilson 1999; Brueckner and Saavedra 2001; Rork, 2003; Revelli 2005). Welfare competition arises from the fear that too generous benefits would lead to an inflow of welfare recipients. Policymakers, thus, compete to lower their welfare benefits, resulting in a ''race to the bottom.'' Figlio, Kolpin and Reid (1999) and Saavedra (2000) among others have found that generosity of welfare benefits is determined strategically based on the potential of interstate migration. In particular, Figlio, Kolpin and Reid (1999) find that states are more responsive to decreases in neighbors' benefits than increases.

Policy interdependence can also be associated with externalities of public goods, e.g. spillover effects. Case, Hines and Rosen (1993) are among the first to incorporate spatial interdependence into analysis and find positive interactions in public expenditures using state level data from the US. The evidence of spillover effects also exists at the local level and beyond U.S. borders. Murdoch, Rahmatian, and Thayer (1993) find positive spillovers in municipal recreational expenditures in California, and Kelejian and Robinson (1993) find positive spillover for county level police expenditures. Further, a number of studies in European countries provide support for spatial interdependence on the expenditure policies (Silva, Beiga, and Portela, 2011; Stastna, 2009; Foucalt, Madies, and Paty, 2008; Werck, Heyndels, and Geys, 2008; Redoano, 2007; Olle 2006; Lundberg, 2006). Revelli (2003), however, points out the importance of incorporating vertical externalities among different layers of authorities when estimating magnitude of horizontal externalities. His paper concludes that the observed spatial autocorrelation in English district expenditures can largely be attributable to common reaction to fiscal policies from the higher level of authority instead of strategic interaction. More recently, Burge and Rogers (2011) also consider both vertical and horizontal fiscal spillovers in local option sales taxes (LOSTs).

Another mechanism driving fiscal policy interaction is political yardstick competition, where imperfectly informed voters use policies of other jurisdictions as a benchmark to evaluate policy efficiency in own jurisdictions. This information asymmetry compels incumbents to mimic policies in other jurisdictions. Evidence supporting the yardstick competition hypotheses has been revealed by Besley and Case

(1995), Bordingnon, Cerniglia, and Revelli (2003), Olle, (2003), and Ermini and Santolini (2010).

Regarding the literature on EDI, substantial empirical research has been devoted to the efficacy of EDI. Peters and Fisher (2004) and Patrick (2014) provide overviews. In contrast, the literature on factors influencing EDI participation or level of spending is very thin. Felix and Hines (2013) investigates characteristics distinguishing the US communities that offer tax-based business incentives from those who do not and what factors are associated with communities that offer TIF versus tax abatements and credits. They find cities and counties are more likely to offer business incentives if they are more heavily populated, located close to state boundaries, have low income, concentration of manufacturing industries, and troubled political cultures. Additionally, they conclude that TIFs are less likely to be used the poorest communities (whose household income is less than $25,000). Man (1999) and Byrne (2005) explicitly control for the possible strategic interaction in municipality’s adoption decision of tax increment financing (TIF). Both papers find evidence of strategic interaction regarding adoption decisions: the former considers cities in Indiana while the latter examines the Chicago metro area. In addition, both papers find that fiscal stress is a determinant of TIF adoption. This paper builds on and extends the work of Byrne (2005) and Felix and Hines (2003) by exploring the strategic interaction in EDI spending at the state level.

3.3 Empirical Approach

3.3.1 Basic Estimation Framework

The public finance literature frequently employs spatial analysis (Brueckner, 2003; Revelli, 2005). When the focus is spatial interaction among jurisdictions, the spatial lag model is often used. The basic estimation framework is illustrated in Equation [1], where the neighboring states' EDI expenditures serve as an additional explanatory variable for home state's incentives spending:

[1] $y_{it} = \rho\sum_{j=1}^{n} w_{ij}y_{jt} + X_{it}\beta + \alpha_i + \theta_t + \varepsilon_{it}$

y_{it} is the per capita incentives spending in state i in year t, while $(I_T\otimes W_N)y_{jt}$ is a weighted average of neighboring states' per capita incentives expenditures. The structure of weighting matrix (W_N) is determined by neighboring criterion described in detail below. X_{it} is a vector containing economic, political and demographic characteristics that are typically thought to affect EDI spending (Byrne, 2005; Felix and Hines, 2013). State fixed effects (α_i) control for time invariant state specific characteristics, while time fixed effects (θ_t) account for common shocks that affect all states in a specific year (e.g. economic cycles and trends in EDI spending).

Equation [1] implies that EDI spending in a particular state-year depends on a weighted average of neighboring states' EDI spending and other conditioning variables. β_2 is the autoregressive parameter, the parameter of interest here. It is also known as the coefficient of the reaction function. When it is estimated to be positive and significant, it implies that states increase their spending on EDI when their neighbors do so, i.e. the existence of incentives competition.

3.3.2 Specification of Weighting Matrix

Identification of neighbors, i.e. weighting matrix (W_N), is key to spatial analysis. Due to the infeasibility of estimating the weighting matrix, it is up to the researcher to specify W prior to estimation (Case, Hines and Rosen, 1993; Brueckner, 2003). Hence, the prior beliefs about how economic agents interact with each other are crucial.

However, there is no clear guidance about what criteria should be used. This paper explores a number of weighting schemes to allow for different patterns of spatial interaction in an attempt to better understand the contributing forces underlying EDI competition.

Geographic proximity has frequently been used as a starting point in spatial economics literature. The major justification lies in that information and resources flow more easily among nearby localities. There are several ways to assign weights based geographic proximity alone.

This paper starts with the most intuitive one, a simple contiguity weighting matrix, which defines neighbors as the ones sharing a common border. The elements of W, therefore, are specified as follows.

$$\omega_{ij} = \begin{cases} 1, \text{ if state i and j shares a border} \\ 0, \text{ if state i and j does not share a border} \end{cases}$$

Consequently, all diagonal elements of W_N, ω_{ii}, are zero. Following the convention in the literature, W_N is row-standardized such that the sum of each row in W is one, meaning the sum of the weights for each state equals one. Take the state of Michigan for example. Each of its neighbors is given a weight of 1/3 because there are three states bordering Michigan (Wisconsin, Indiana, and Ohio).

An extension of the simple contiguity weighting matrix is the distance-based weighting matrix, where state i's EDI spending is affected by EDI expenditures of all the other states in the sample, but in inverse proportion to their distances to i. Inverse distance weights allow the effect to decrease with distance. Again, all diagonal elements of W are zeros. Off-diagonal elements ω_{ij} are defined as $\omega_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_j \frac{1}{d_{ij}}}$, where d_{ij} is the point distance between centroids of two states.

A variety of weighting matrices other than simply geography-based ones have also been adopted in the literature. Following Rork (2003) and Baicker (2005), I also consider population contiguity weighting matrix. This refines the simple contiguity weighting matrix by assigning weights based on the relative size of population among bordering states: states with higher population are assigned with greater weights. [28] Mathematically, off-diagonal elements are defined as $\omega_{ij} = \frac{Population j}{\sum_j Population j}$, with i ≠ j. [29] Consider the state of Michigan again. The weight assigned to Ohio, for example, is its population divided by the sum of the populations of Wisconsin, Indiana and Ohio. Hence, the weight or importance of Ohio as Michigan's neighbor is close to 1/2 instead of 1/3 due to its relative larger population.

Further, it is possible that policy interaction in EDI spending is less determined by geographic proximity but more by economic similarity. States may watch more closely and subsequently be more responsive to the actions of states that share similar economic characteristics regardless of geographic distance. To this end, I experiment with weights based on economic proximity as well. I construct an inverse income distance weighting matrix, which is the same as the inverse distance weighting matrix above except that d_{ij} is replaced with the Euclidean distance in average per capita

[28] The population for each state is averaged over the entire sample period (2000-2012). Therefore, W is constructed to be constant over time.

[29] In addition to contiguity weights based on population, this paper also experimented with weighing schemes based on income, corruption, manufacturing share of employment, infrastructure spending, education and higher education spending.

income between states i and j. Using Euclidean distance helps to mitigate the endogeneity of W (Xiao, 2014). Again, Euclidean distances based on corruption, manufacturing share of employment, infrastructure spending, education and higher education spending are also considered.

3.3.3 Estimation Problems

Three problems arise in the estimation of the spatial econometric framework in equation [1]: endogeneity of neighbors' incentives spending, potential spatial error dependence, and possible correlation between other control variables and the error term (Brueckner, 2003).

In the presence of strategic interaction when states do react to each other's incentives expenditures, incentive expenditures in different states are jointly determined in Nash equilibria. This simultaneity leads to the correlation of WY_{it} and the error term on the right-hand sided of equation [1]. Endogeneity causes the OLS estimator to be both biased and inconsistent. Existing literature addresses endogeneity using a Maximum likelihood (MLE) estimator, which removes the dependent variables on the RHS through inverting the system, or an instrumental variable (IV) approach (Brueckner, 2003).

Possible spatial error dependence further complicates the estimation of equation [1]. This problem arises when spatially interdependent variables are omitted. When this is unaddressed in the estimation, false evidence of interdependence may occur as a result. In this circumstance, the error vector follows a spatial lag process as below, υ is white noise.

[2] $\varepsilon = \pi W\varepsilon + \upsilon$

MLE is one way to circumvent this problem. The computational challenge of MLE coupled with the Jarque-Bera LM tests' rejection of the null hypothesis that errors are normally distributed for my sample dismissed MLE as an appropriate procedure (Gebremariam et al, 2012). IV estimation provides an alternative that does not require distributional assumptions on the error term. The IV estimator is argued to be consistent even in the presence of spatial error dependence (Kelejian and Prucha, 1998). Therefore, I adopt IV estimator in this paper. To this end, an instrument correlated with neighbors' EDI but uncorrelated with the error term needs to be found. One commonly used source of variation is neighbors' control variables (X_{it}). Weighted average of neighbors' control variables are created as instruments using the same weighting matrix (Brueckner, 2003).

A third problem in the estimation of [1] is the potential correlation of other control variables (X_{it}) and the error term, which has been typically ignored by previous studies. Brueckner (2003) admits that finding suitable instruments is a feasible yet very difficult endeavor. The use of panel data, however, is suggested as an alternative. All time invariant characteristics are captured in individual specific intercepts. The correlation is largely removed even though some might remain due to time varying unobserved characteristics not being purged by mean deviation transformation.[30] To further mitigate this concern, I estimate Equation [3], which uses one year lagged values of control variables that are thought most likely to be endogenous (Brown et al, 2009).[31]

[30] In addition, Brueckner (2003) claims that panel data helps to mitigate the concern of spatial error dependence because fixed effect would absorb much of the error interdependence.
[31] All covariates but federal grants enter the regression as one-year lagged values. For one, EDI spending does not seem to influence federal grants conceptually, hence there does not seem to be need to lag the variable of federal grants like others. For another, results do not change qualitatively when federal grants in the previous year are used in the regression except that coefficients on lagged federal grants are no longer statistically significant. Whether personal income in incorporated as lagged value or not does not

$$[3]\ y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + X_{it-1}\beta + \alpha_i + \theta_t + \varepsilon_{it}$$

3.4 Data

3.4.1 Measures of Economic Development Incentives

Given that the focus of this paper is to investigate if states' incentives expenditures are affected by those of their neighbors, good measures of incentives spending are critical. However, existing literature establishes that ideal measures for EDI do not exist (Fisher and Peters, 1997; Patrick, 2014). Program counts, a frequently used measure in earlier studies, can be severely misleading about the generosity of EDI offered, and are thus inappropriate for the purpose of this paper. Another commonly adopted measure is states' economic development agency spending. This too is unsatisfying because development agency funds can be used for noneconomic activities and funding for EDI may come from alternative sources.[32] Conclusions based on a measure like this are suspicious.

As an alternative, my study exploits Subsidy Tracker, a new exciting database on economic development incentives gathered by Good Jobs First.[33] Subsidy Tracker is the first national search engine for state and local economic development incentives. It brings together public records of incentives granted to businesses and includes 12 broad categories of both tax and non-tax incentive programs (tax credits/rebates, property tax abatements, megadeal, grants/low-cost loans, enterprise zones, tax increment financing, training reimbursements, cost reimbursements, infrastructure assistance, industrial

affect results qualitatively except that coefficient estimates are negative and significant when it is entered as contemporaneous values.

[32] Gorin (2008) provides an excellent example from Oklahoma. Notably, the data source for state economic development agency expenditure, i.e. the website for the National Association of State Development Agencies (NASDA), does not exist anymore.

[33] Good Jobs First (GJF) is a nonprofit, nonpartisan group that promotes accountability in economic development. For more information, please refer to http://www.goodjobsfirst.org/about-us.

revenue bonds, tax credits/rebates and grants, tax credits/rebates and property tax abatements). It includes the actual dollar value of incentives granted, providing a measure of EDI spending that was not available for previous research.

Despite not being inclusive of all incentives programs and the granted values, it is still the most comprehensive database of incentives available (Kenyon, Langley, and Paquin, 2012).[34] This paper utilizes the Subsidy Tracker database (June 09, 2014 version) and aggregates subsidy values by state-year so that each observation is the value of subsidies granted by a state in a specific year.[35]

3.4.2 Other Variables

The conditioning variables in X_{it} of equation [1] largely follow previous literature and consist of economic, political and demographic characteristics of states (Byrnes, 2005; Felix and Hines, 2013).

Since EDI is extensively used by policymakers for employment promotion, we would expect states with high unemployment and substantial manufacturing employment to be more active in incentives use. Unemployment rate and manufacturing share of employment are, therefore, included in addition to per capita federal grants and per capita income which account for resources available to state and local governments. Following Felix and Hines (2013), per capita state tax revenue, top statutory state corporate income tax rate, general state sales tax rate, top statutory state personal income tax rate are incorporated because how much EDI states are willing and able to

[34] Harpel (2014) has a detailed discussion about Subsidy Tracker.
http://www.smartincentives.org/blogs/blog/14754093-good-jobs-first-and-subsidy-tracker-2-0.

[35] One downside of Subsidy Tracker database is that it did not try to annualize the amount of award for multi-year packages. But since it is consistent for all states and years and the focus of this paper is to examine if states are responsive to their neighbors' EDI spending, this issue should not affect my results qualitatively.

offer depend on existing tax structure as well. As pointed out in the literature, public goods like infrastructure also play a role in business location decisions (Fisher and Peters, 1997). We would expect states with better infrastructure to be more attractive to the businesses, so they may not need to offer as much incentives to lure investments.[36] Therefore, I include the 'infrastructure' variable, expressed as a percentage: core infrastructure spending divided by total direct expenditures by state and local governments.[37]

Certain political variables have also been hypothesized to affect incentives use. More specifically, Felix and Hines (2013) find that communities with troubled political culture are more likely to offer tax-based incentives; while Jansa and Gray (2014) uncover evidence that more campaign contributions from business results in higher subsidy spending. My specification includes 'corruption' variable, calculated as the number of federal public corruption convictions per 1,000,000 residents in each state (Felix and Hines, 2013). Election cycles could also contribute to variations in EDI use, which is discussed in more detail in Section V.

For demographic characteristics, the fraction of population above 65 years old is included because the elder population may be more active voters (Rork, 2003). Hypothesis tests indicate that population density and percentage of population below 15 are not determinants of EDI spending; therefore, they are dropped from the regression.

[36] Chris Cummiskey, head of Georgia's Department of Economic Development, believes that "Georgia would pick up most of the business in the southeast even without incentives given its infrastructure". "Sweet land of subsidy": http://www.economist.com/news/united-states/21576669-downturn-has-forced-states-be-savvier-and-more-careful-about-providing-tax.

[37] Following Felix and Hines (2013), core infrastructure comprises of air transportation, general public buildings, regular highways, toll highways, private transit subsidies, parking facilities, sewerage, solid waste, sea and inland port facilities, water utilities, electric utilities, gas utilities, and transit utilities.

When added, estimated coefficients are insignificant and do not affect overall results qualitatively.

Given that the use of EDI can potentially affect the above-mentioned conditioning variables, one year lag of all covariates except federal grants are used in estimation to avoid contemporaneous correlation between control variables and the error term.

3.4.3 Data Sources and Summary Statistics

Government finance data (federal grants, infrastructure spending, state tax revenue), manufacturing share of employment and demographic data are obtained from US Census, while personal income and unemployment rates are from the Bureau of Economic Analysis (BEA). Top statutory state corporate income tax rate and general state sales tax rate data are drawn from Tax Foundation, while top statutory state personal income tax rate data are collected from Tax Policy Center. The U.S. Department of Justice provides reports of federal public corruption convictions. Control variables are matched with EDI data. All dollar values are expressed in per capita and converted to real values (using 1982—1984 as the base year). The requirement of a balanced panel for estimation restricts the sample to 22 states over the period 2000-2011. Figure 3.1 and Table 3.1 provide a map and a list of states covered in this sample, respectively. Geographically, the sample covers states mostly in the Northeast, Midwest and the South region. Economically, these 22 states account for about 60% of all EDI offered from 2000 to 2011 in US states according to the Subsidy Tracker database. Table 3.2 provides variable descriptions and data sources.

Summary statistics are shown in Table 3.3. The dataset contains 264 observations. The descriptive statistics indicate considerable variation in EDI spending, personal income as well as other control variables. A closer examination of the sample reveals that per capita EDI spending ranges over the time period from $0.004 (Louisiana in 2010) to $351.87 (Louisiana in 2004) with an average of $18.77 across all states and years. The states having high EDI spending in all years are Louisiana, Michigan, Kentucky, and New York. This is somewhat expected as Michigan and New York also have the highest manufacturing share of employment during the sample period, whereas New York and Louisiana are also among the top states in receiving federal grants. The average manufacturing share of employment is 12.92 percent, ranging from 4 to 24 percent. Corruption rate varies extensively with the average being 3.7 convictions per 1,000,000 residents. The highest occurred in Virginia in 2007 and the lowest was in Michigan in 1999. Infrastructure spending as a percentage of total spending remains pretty stable for sample states across the years, with average about 15 percent.

3.5 Results

As mentioned in Section III, instrumental variable approach is chosen over MLE to estimate the spatial lag model [3] because the Jarque-Bera test rejects the hypothesis of normally distributed error terms.[38] Home states' EDI expenditures are regressed on neighboring states' EDI spending and conditioning variables. The regression coefficients and their associated standard errors (in parentheses) are reported in Table

[38] When the baseline model is estimated using MLE, overall results remain qualitatively similar. Compared with IV estimation, coefficients on the key parameter (ρ) are generally smaller, ranging from 0.11 to 0.187 depending on the definition of neighbors.

3.4.[39] Column [1] shows the baseline results using simple contiguity matrix and indicates that states do respond to their neighboring states' incentives expenditures. A dollar increase from the average neighbor's EDI spending raises the home state's incentives spending by approximately 57 cents. In terms of elasticity, states increase their incentives spending by 0.54% in response to a 1% increase the average neighbor's incentives spending.

As mentioned above, there is good reason to believe that states consider others with similar economic structure as salient competitors. Hence, this papers experiments with a variety of different definitions for "neighborliness". Columns [2] to [9] of Table 3.4 reports estimated coefficients under inverse distance weights, contiguity weights based on population, personal income, median household income, corruption, manufacturing share of employment, infrastructure spending, education and higher education spending respectively. Table 3.5 (except the last column, [8]) presents results under Euclidean distance weights based on the same political and economic characteristics in Table 3.4. The major difference is that in Table 3.5 every state is assumed to be a neighbor of the other states, while in Table 3.4 contiguity weights consider only bordering states as neighbors. The coefficients from various weighting schemes are similar in sign, magnitude, and significance. Overall the models explain about 35 percent of the variation in state-level per capita EDI spending.

Regardless of definitions of neighbor, estimates for the parameter of interest is positive and statistically different from 0, ranging from 0.37 under population contiguity weights to 0.81 under inverse distance weights, which means that a dollar increase in the average neighboring states' incentives spending induces an increase in

[39]Asterisks denote significance levels at the 1% (***), 5% (**), and 10% (*).

incentives spending in the home state of between 37 cents to 81 cents.[40] This result suggests that state and local governments use EDI to lure business to locate or expand within their borders. When a state increases EDI spending, it puts pressure on nearby states and propels them to spend more on EDI as well. The corresponding elasticity ranges from 0.37 to 0.83. The elasticity estimates are all less than 1, which says despite states increase their EDI spending when their neighbors do so, the response is relatively unresponsive to neighboring states' increase in incentives spending.

Despite overall results confirm the existence of policy interaction in EDI spending with most estimates clustering 0.56 and 0.6, the smallest estimate comes under population contiguity weights. It is also worth noting that coefficient estimates considering neighbors as ones beyond immediate borders (reported in Table 3.5) are generally larger than those of Table 3.4.

Given that the focus of the paper is the spatial autoregressive parameter, I focus on the marginal effects of the control variables on own state's dependent variable instead of computing direct and indirect effects. Coefficient estimates for the conditioning variables generally have the expected signs and similar magnitudes regardless of weighting schemes.

We can see that regardless of the choice of weighting schemes, grants positively affect how much EDI are offered. A higher unemployment rate and manufacturing share of employment in the previous year have been found to be associated with the more EDI spending in the current year, consistent with the findings of Felix and Hines (2013). This supports the popular belief that job creation is a major reason for

[40] These estimates are of comparable magnitudes to literature on spatial interaction. For example, Case, Hines and Rosen (1993) find that states respond to a dollar increase in their neighbors' spending by over 70 cents, whereas Baicker (2005) estimates the magnitude to be almost 90 cents.

policymakers to offer EDI. The only demographic characteristic that significantly affects EDI spending is the percentage of population above 65. The lagged elder population proportion is negatively associated with incentives spending. The coefficients on tax variables are not statistically significant except top state personal income tax rates. It seems that states with higher personal income tax rates offer less incentives. The other lagged control variables do not have statistically significant effects on incentives spending.[41]

3.6 Robustness Checks and Extensions

Given the significant results of all the different neighborliness definitions, some might suspect that the idiosyncrasy of the data or the spatial econometrics framework will always produce a statistically significant coefficient estimate for the autoregressive parameter. Following Case, Hines and Rosen (1993), I run a falsification test by constructing a weighting matrix based on a ridiculous neighboring criterion, alphabetical order of state names. More specifically, ω_{ij} equals 1 if states i and j are next to each other in alphabetical order list of states. In the case where a state's alphabetical neighbors are not included in my sample, its neighbor is designated as the state immediately before or after its alphabetical neighbor. Table 3.5 Column [8] reports regression results based on this "false" spatial weighting matrix. The coefficient estimate on neighboring states' incentives spending is no longer statistically significant, while coefficients for control variable still have the same signs as baseline estimation.

[41] When corruption and infrastructure spending are included as contemporaneous values, the former has a positive effect on incentives spending, while the latter has a negative effect. This indicates that states with more troubled political culture spend more on EDI, while better infrastructure states spend less, consistent with the findings of Felix and Hines (2013).

This further strengthens our confidence in the evidence of incentives competition. It is unlikely obtained due to the arbitrary nature of the data or econometrics method.

In addition to falsification test, I also extend the baseline model in an attempt to investigate whether incentives competition has become more intense in recent years, especially after the 2008 financial crisis.

According to *the Economist*, "The cash crunch following the downturn led some states to spend more on economic development in order to lure businesses. It has led others to save precious funds by tightening economic development budgets." [42] It would be interesting to investigate if incentives competition among states has intensified or weakened since the 2008 financial crisis. To this end, the baseline regression model is modified as follows.

[4] $y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \gamma D_{2008} \sum_{j=1}^{n} w_{ij} y_{jt} + X_{it-1}\beta + D_{2008} + \alpha_i + \varepsilon_{it}$

D_{2008} is a dummy variable that equals 1 for years after and including 2008, 0 otherwise. WY_{2008} is the product of neighbors' EDI spending and D_{2008}. If the coefficient in front of this interaction term, γ, is positive and significant, it indicates that states compete against each other more fiercely in EDI spending after 2008. The reported coefficient estimates in Tables 3.6 and 3.7 (under contiguity and Euclidean weighting matrices respectively), however, fail to suggest more intense competition after year 2008 for the sample states.

It is possible that competition did get more intense after the crisis but with a lag. To test this possibility, [4] is modified as follows.

[5] $y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \gamma' D_{2009} \sum_{j=1}^{n} w_{ij} y_{jt} + X_{it-1}\beta + D_{2009} + \alpha_i + \varepsilon_{it}$

[42] "Sweet land of subsidy": http://www.economist.com/news/united-states/21576669-downturn-has-forced-states-be-savvier-and-more-careful-about-providing-tax.

D_{2009} is a dummy variable that assigns years starting 2009 as 1, 0 otherwise. The second term on RHS is the product of neighbors' EDI spending and D_{2009}. Again, results reported in Tables 3.8 and 3.9 are very similar to those in Tables 3.6 and 3.7 (γ' insignificant). The estimates do not point to more intense competition after the 2008 financial crisis. Although not reported in the main results table, coefficients for year dummies between 2009 and 2010 are negative and significant. This seem to indicate states do not have enough to spend on EDI, which might be why we did not find more intense competition after the financial crisis. The possibility that more or less intense competition after the 2008 financial crisis cannot be ruled out completely, but I did not find any evidence using the above data and sample.

Another question that can be addressed is: Is EDI competition affected by political cycle? The nature of strategic interaction is very hard to pin down as different sources of competition (such as tax competition and yardstick competition) have similar effects.[43] This paper does not claim to disentangle the two, but rather makes a very first attempt to see if political cycle plays a role in states' EDI spending decision. Following Ermini and Santolini (2010), the following changes have been made to the baseline model to see if state governor election cycle drives incentives competition, where $D_{election}$ is a dummy variable assigns governor election years related to change in governor as 1 and 0 otherwise.[44]

[43] Tax competition arises from jurisdictions compete over a mobile recourse (Wilson, 1999; Rork, 2003). Yardstick competition arises when voters have imperfect information and thus evaluate incumbents by using other jurisdictions' actions as benchmark. Hence, yardstick competition produces copycat behavior, which is indistinguishable from tax mimicking (Brueckner, 2003; Revelli, 2005). But for yardstick competition, this mimicking behavior is more apparent in election years (Besley and Case, 1995; Olle, 2003, Bordignon et al., 2003).

[44] Mimicking behavior is expected to be less pronounced if politicians cannot run for re-election, possibly due to term limits or retiring, so those years are also assigned to be 0 for $D_{election}$.

[6] $y_{it} = \rho\sum_{j=1}^{n} w_{ij}y_{jt} + \delta D_{election} \sum_{j=1}^{n} w_{ij}y_{jt} + X_{it-1}\beta + D_{election} + \alpha_i + \varepsilon_{it}$

The variable 'election' is the interaction of neighbors' incentives spending and governor election year dummy ($D_{election}$). We would expect the coefficient on 'election' to be positive and significant if election cycle plays a part in EDI competition. Results are reported in Tables 3.10 and 3.11 δ remains statistically insignificant and negative mostly, rejecting yardstick competition as an explanation. The coefficient estimates of $D_{election}$ are positive although not distinguishable from 0 in most cases, meaning states spend more on incentives in governor election years. Concerned that policymakers may respond to neighbors' policy in the year that precedes election, Tables 3.12 and 3.13 presents estimates of the model similar to [5] but with lagged governor election interacting with neighbor's EDI spending (l_election). Still, no significant relationship has been found (δ' remains statistically insignificant). This may change if more states and years are covered in the sample. Future research is needed to explore this question with better data coverage.

3.7 Conclusion

As the popularity of EDI grows, better understanding of EDI and related spending decisions is warranted. Most existing empirical studies, nevertheless, do not take strategic interaction into account when modelling EDI use. This paper examines whether EDI spending decisions in U.S. and the evidence shows that states exhibit some degree of interdependence in EDI spending decisions. That is, states react to neighbor's increases in EDI spending by increasing their own EDI expenditures. This result is robust to numerous neighbor definitions.

Isolating the source of strategic interaction is very hard: two underlying theoretical frameworks produce equivalent reduced form models for empirical estimation. However, this analysis suggests that the competition for mobile businesses (which supposedly brings investment and jobs) is a more likely driver of EDI competition among states, given that I fail to find statistically significant influence of election cycles. This paper also tests if states compete more fiercely against each other after the most recent financial crisis. No such evidence has been found. EDI spending in US states is influenced by neighbors' spending, but competition is not the sole impetus. EDI spending has also been found to be correlated with states' own economic characteristics such as unemployment rate, manufacturing share of employment.

The use of state-level data in a spatial econometric framework is a contribution of this study. Greater understanding of EDI spending at the state level provides insights for policymakers and adds to the heated discussion about incentives use. Utilizing Subsidy Tracker database and panel data across states provide more generalizable compared with studies that focus on a single geographic area or a specific type of incentives. This paper leaves several questions unanswered: how does strategic interaction of specific types of EDI differ from each other? Does the EDI spending on big projects cause yardstick competition among states? Will states' response be different for decreases in neighbor's EDI spending from increases? Future research with more detailed data and sample coverage is needed to address these questions and validate findings of this paper.

Figure 3.1: Sample Coverage of States

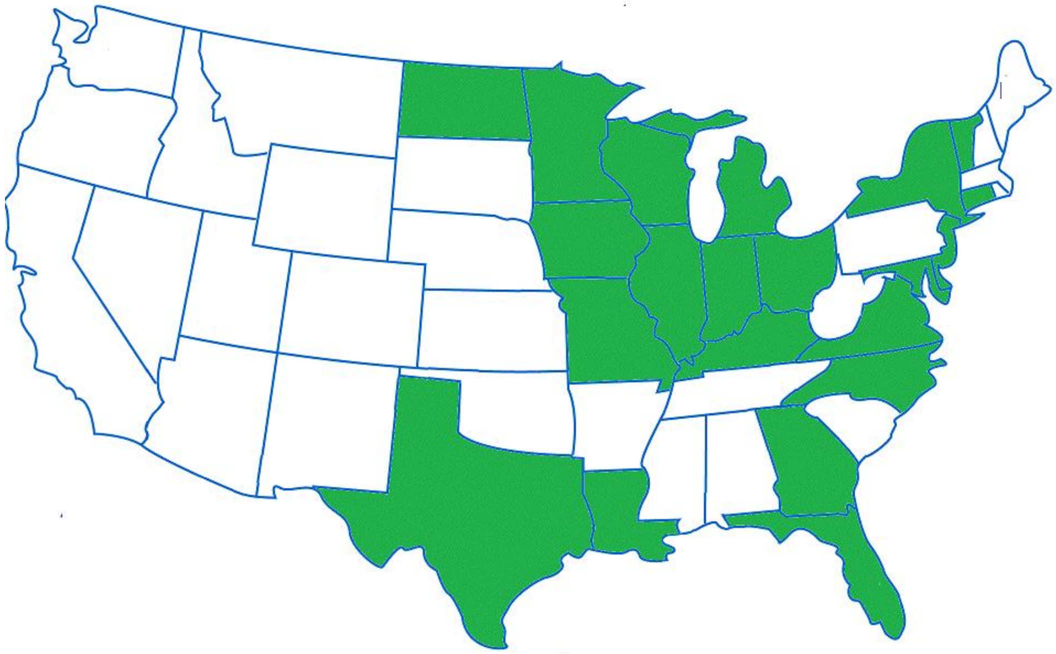


Table 3.1: List of Sample States (count = 22)

1	Connecticut	12	Minnesota
2	Delaware	13	Missouri
3	Florida	14	New Jersey
4	Georgia	15	New York
5	Illinois	16	North Carolina
6	Indiana	17	North Dakota
7	Iowa	18	Ohio
8	Kentucky	19	Texas
9	Louisiana	20	Vermont
10	Maryland	21	Virginia
11	Michigan	22	Wisconsin

Table 3.2: Variable Names and Data Sources

Variables	Description	Data Sources
incentives	Per capita EDI spending ($)	Subsidy Tracker (GJF)
grants	Per capita federal grants ($)	U.S. Census
l_income	Per capita personal income ($)	Bureau of Economic Analysis (BEA)
l_jobless rate	Unemployment rate (%)	Bureau of Economic Analysis (BEA)
l_above 65	Percentage of elder population (%)	U.S. Census
l_corruption	Convictions per 1,000,000 residents	U.S. Department of Justice
l_manufacturing	Manufacturing share of employment ($)	U.S. Census
l_infrastructure	Infrastructure spending (%)	U.S. Census
l_tax revenue	Per capita state tax revenue ($)	U.S. Census
l_sales tax rate	State general sales tax rate (%)	Tax Foundation
l_corporate_rate	Top statutory corporate income tax rate (%)	Tax Foundation
l_personal_rate	Top statutory personal income tax rate (%)	Tax Policy Center

Note: "l_" in front of variable names represent "lagged" and refers to one year lag value of the above variables

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Table 3.3: Summary Statistics (n=264)

Variables	Mean	Std. Dev.	Min	Max
incentives	18.767	38.707	0.004	351.874
grants	715.4	254.6	250.0	1585.9
l_income	18044.8	2636.7	13480.1	26945.9
l_jobless rate	5.3492	1.9744	2.2	13.3
l_above 65	12.87	1.55	9.55	18.14
l_corruption	3.70	2.74	0.00	25.05
l_manufacturing	12.92	4.67	4.10	24.70
l_infrastructure	14.98	2.23	9.96	20.92
l_tax revenue	48.11	5.63	33.32	66.88
l_sales tax rate	5.07	1.40	0	7
l_corporate_rate	6.34	3.37	0	12
l_personal_rate	5.16	3.00	0	12

Notes:

(1) All dollar figures have been converted to real values, deflated by CPI (1982-84=100).
(2) All dollar values are on a per capita basis.
(3) "l_" in front of variable names represent "lagged" and refers to one year lag value of the above variables.

Table 3.4: Basic Results (Contiguity Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Ws	Binary	Inverse_dist	Pop	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.568***	0.810**	0.374**	0.746**	0.559***	0.564***	0.567***	0.561***	0.569***	0.575***
	(0.182)	(0.341)	(0.153)	(0.344)	(0.180)	(0.179)	(0.179)	(0.181)	(0.181)	(0.176)
Grants	0.042***	0.052***	0.047***	0.055***	0.043***	0.039***	0.043***	0.042***	0.042***	0.041***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
l_income	0.005	0.006	0.004	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
l_jobless rate	5.940**	5.138*	6.368**	5.333*	5.962**	5.598**	5.981**	5.955**	5.913**	5.894**
	(2.755)	(2.932)	(2.797)	(2.938)	(2.767)	(2.807)	(2.744)	(2.732)	(2.752)	(2.736)
l_above 65	-21.177**	-19.040*	-19.139*	-19.101*	-20.656**	-20.128**	-21.580**	-21.947**	-21.252**	-21.845**
	(9.584)	(9.728)	(9.707)	(9.756)	(9.608)	(9.660)	(9.572)	(9.541)	(9.572)	(9.543)
l_corruption	0.990	1.580	1.233	1.699	0.988	1.021	0.965	0.999	0.984	0.986
	(1.169)	(1.170)	(1.183)	(1.171)	(1.174)	(1.180)	(1.166)	(1.159)	(1.167)	(1.160)
l_manufacture	6.142**	5.693*	6.815**	5.785*	6.306**	6.199**	5.892**	6.080**	6.090**	6.035**
	(2.849)	(3.008)	(2.879)	(3.029)	(2.852)	(2.878)	(2.857)	(2.831)	(2.847)	(2.832)
l_infrastructure	4.005	3.554	2.959	3.460	4.042	4.128	4.012	4.177	4.134	4.534
	(3.372)	(3.464)	(3.492)	(3.482)	(3.387)	(3.411)	(3.362)	(3.341)	(3.365)	(3.345)
l_tax revenue	0.026	-0.060	0.206	-0.069	0.022	0.029	0.063	-0.003	0.035	0.000
	(1.141)	(1.170)	(1.159)	(1.175)	(1.146)	(1.154)	(1.136)	(1.132)	(1.139)	(1.133)
l_sales tax rate	202.545	141.699	120.823	169.442	232.042	156.687	137.238	228.513	202.304	265.545
	(890.985)	(914.256)	(912.861)	(915.811)	(894.464)	(903.001)	(890.148)	(882.785)	(889.666)	(883.644)
l_corporate_ rate	-61.938	-33.781	-77.230	-42.260	-54.471	-36.487	-73.887	-65.749	-61.472	-58.415
	(101.656)	(104.849)	(103.559)	(104.725)	(102.216)	(103.410)	(101.338)	(100.759)	(101.512)	(101.007)
l_personal_rate	-390.661**	-522.222***	-429.377**	-540.989***	-395.429**	-383.243**	-394.654**	-388.812**	-391.872**	-389.684**
	(177.116)	(179.509)	(179.244)	(181.240)	(177.712)	(179.581)	(176.365)	(175.758)	(176.771)	(175.830)
Ajusted R Square	0.351	0.324	0.327	0.321	0.345	0.335	0.355	0.363	0.353	0.360
Elasticity	0.543	0.817	0.374	0.745	0.536	0.542	0.558	0.531	0.545	0.554

Note that ‘Inverse_dist’ stands for inverse geographic distance while ‘MedianHH’ refers to median household income. Same as below.

Table 3.5: Basic Results (Euclidean Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Euclidean Ws	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu	Falsification
Neighbor's EDI	0.594*	0.626*	0.613*	0.644*	0.791**	0.684*	0.639*	-0.193
	(0.309)	(0.342)	(0.360)	(0.361)	(0.311)	(0.398)	(0.367)	(0.152)
Grants	0.053***	0.054***	0.055***	0.051***	0.053***	0.056***	0.055***	0.048***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)
l_income	0.005	0.005	0.004	0.003	0.006	0.005	0.004	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
l_jobless rate	6.198**	5.713**	5.909**	5.481*	5.213*	5.642*	5.601*	7.946***
	(2.831)	(2.891)	(2.904)	(3.045)	(2.926)	(2.987)	(2.963)	(2.758)
l_above 65	-18.925*	-18.412*	-18.724*	-16.588*	-20.153**	-17.640*	-19.203*	-14.383
	(9.700)	(9.605)	(9.725)	(9.964)	(9.850)	(9.814)	(9.779)	(9.790)
l_corruption	1.554	1.606	1.688	1.749	1.870	1.687	1.700	2.121*
	(1.167)	(1.156)	(1.167)	(1.200)	(1.180)	(1.182)	(1.170)	(1.189)
l_manufacture	6.164**	5.705*	5.890*	5.097	5.368*	6.483**	6.065**	8.156***
	(2.992)	(3.081)	(3.102)	(3.348)	(3.052)	(3.012)	(3.060)	(2.799)
l_infrastructure	3.491	3.561	3.555	3.374	3.855	3.508	3.265	5.482
	(3.469)	(3.441)	(3.483)	(3.593)	(3.479)	(3.532)	(3.522)	(3.459)
l_tax revenue	0.200	0.000	0.233	0.414	-0.138	0.216	0.081	0.294
	(1.158)	(1.158)	(1.160)	(1.195)	(1.183)	(1.176)	(1.169)	(1.143)
l_sales tax rate	157.349	107.506	175.078	82.953	180.961	193.586	194.296	233.666
	(913.239)	(911.886)	(916.613)	(949.910)	(919.447)	(926.637)	(917.018)	(903.548)
l_corporate_ rate	-28.225	-37.484	-58.589	-31.482	-30.574	-69.951	-45.497	-51.133
	(105.567)	(104.024)	(103.813)	(108.685)	(105.777)	(104.972)	(104.817)	(103.097)
l_personal_rate	-513.632***	-532.987***	-524.578***	-548.227***	-521.028***	-546.176***	-530.586***	-425.424**
	(178.785)	(178.968)	(180.375)	(187.540)	(180.881)	(184.938)	(181.313)	(180.474)
Ajusted R Square	0.329	0.340	0.326	0.287	0.312	0.308	0.322	0.346
Elasticity	0.628	0.627	0.618	0.643	0.833	0.674	0.649	-0.196

Table 3.6: Extensions 1.1 (Contiguity Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Ws	Binary	Inverse_dist	Pop	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.651***	0.839***	0.435**	1.222*	0.651***	0.438**	0.660***	0.641***	0.658***	0.653***
	(0.230)	(0.318)	(0.195)	(0.656)	(0.238)	(0.217)	(0.225)	(0.217)	(0.229)	(0.218)
γ	0.240	0.933	0.458	-0.802	0.222	0.528	0.096	0.281	0.214	0.205
	(0.553)	(0.659)	(0.602)	(1.774)	(0.554)	(0.462)	(0.543)	(0.548)	(0.548)	(0.507)
Grants	0.036***	0.039***	0.039***	0.050***	0.037***	0.036***	0.038***	0.036***	0.036***	0.036***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
l_income	0.002	0.003**	0.002	0.003*	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	0.994	0.111	1.364	1.162	1.018	0.794	1.166	0.919	0.980	0.886
	(1.820)	(1.857)	(1.812)	(1.855)	(1.837)	(1.811)	(1.808)	(1.805)	(1.819)	(1.814)
l_above 65	2.277	0.814	2.150	1.830	2.275	1.479	2.808*	2.133	2.370	2.394
	(1.581)	(1.500)	(1.589)	(1.717)	(1.604)	(1.540)	(1.611)	(1.546)	(1.586)	(1.572)
l_corruption	0.477	0.858	0.554	1.176	0.501	0.643	0.522	0.456	0.487	0.539
	(0.903)	(0.883)	(0.905)	(0.913)	(0.909)	(0.889)	(0.902)	(0.896)	(0.902)	(0.895)
l_manufacture	1.548**	1.678**	1.680**	2.144**	1.544**	1.597**	1.567**	1.564**	1.571**	1.582**
	(0.688)	(0.675)	(0.688)	(0.844)	(0.693)	(0.678)	(0.687)	(0.681)	(0.687)	(0.683)
l_infrastructure	1.787	1.212	1.985	2.305	1.875	1.913	1.622	1.697	1.742	1.644
	(1.473)	(1.495)	(1.503)	(1.528)	(1.480)	(1.429)	(1.472)	(1.463)	(1.469)	(1.452)
l_tax revenue	-0.276	-0.882	-0.183	-0.613	-0.255	-0.251	-0.218	-0.309	-0.266	-0.295
	(0.821)	(0.848)	(0.826)	(0.881)	(0.828)	(0.808)	(0.817)	(0.814)	(0.821)	(0.817)
l_sales tax rate	-228.092	-76.909	-215.634	-335.771	-234.371	-182.260	-257.293	-214.727	-233.842	-228.046
	(210.288)	(211.049)	(218.898)	(291.402)	(212.727)	(202.412)	(210.250)	(207.522)	(210.095)	(208.929)
l_corporate_ rate	52.911	88.385	50.276	97.838	60.901	90.102	38.614	47.199	51.739	55.023
	(78.970)	(76.345)	(79.458)	(80.783)	(79.445)	(77.712)	(79.537)	(78.323)	(79.056)	(78.669)
l_personal_rate	-125.103	-105.015	-94.365	-203.365	-132.169	-119.179	-138.540	-119.269	-131.792	-140.002
	(93.864)	(94.803)	(95.652)	(133.911)	(93.985)	(89.223)	(95.751)	(93.392)	(93.977)	(92.937)
Ajusted R Square	0.360	0.393	0.356	0.318	0.350	0.375	0.361	0.373	0.360	0.365

Table 3.7: Extensions 1.1 (Euclidean Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Euclidean Ws	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.815**	0.643*	0.907**	0.680	0.787**	0.846*	0.395
	(0.411)	(0.376)	(0.386)	(0.433)	(0.384)	(0.498)	(0.401)
γ	-0.140	0.168	-0.451	0.521	-0.243	0.014	0.839
	(0.896)	(0.889)	(1.072)	(0.974)	(0.898)	(1.068)	(0.680)
Grants	0.049***	0.050***	0.050***	0.048***	0.050***	0.051***	0.052***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
l_income	0.003*	0.002	0.002	0.002	0.003*	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	1.958	1.971	1.784	1.959	1.641	1.526	1.909
	(1.784)	(1.759)	(1.804)	(1.857)	(1.832)	(1.861)	(1.819)
l_above 65	1.438	1.507	1.785	1.539	1.529	1.761	1.443
	(1.531)	(1.520)	(1.581)	(1.579)	(1.572)	(1.569)	(1.536)
l_corruption	1.182	1.088	1.118	1.108	1.273	1.121	1.085
	(0.901)	(0.885)	(0.904)	(0.932)	(0.911)	(0.912)	(0.899)
l_manufacture	1.947***	1.780**	2.018***	1.366*	1.898***	1.910***	1.682**
	(0.739)	(0.713)	(0.751)	(0.755)	(0.710)	(0.734)	(0.715)
l_infrastructure	2.005	2.013	2.336	1.712	2.460*	2.185	1.921
	(1.467)	(1.449)	(1.475)	(1.600)	(1.461)	(1.488)	(1.454)
l_tax revenue	-0.332	-0.245	-0.237	0.200	-0.314	-0.078	-0.058
	(0.845)	(0.831)	(0.837)	(0.832)	(0.858)	(0.843)	(0.842)
l_sales tax rate	-290.226	-237.571	-313.039	-252.451	-275.273	-275.565	-168.790
	(221.640)	(218.835)	(235.792)	(235.953)	(232.517)	(225.231)	(208.713)
l_corporate_ rate	113.122	97.750	89.597	132.812	101.474	83.140	89.115
	(80.386)	(79.247)	(79.836)	(85.106)	(79.987)	(80.791)	(79.441)
l_personal_rate	-153.775	-138.233	-166.003	-136.240	-162.380	-139.956	-85.141
	(106.805)	(106.294)	(105.734)	(106.542)	(103.877)	(104.462)	(99.850)
Ajusted R Square	0.339	0.364	0.333	0.290	0.336	0.319	0.339

Table 3.8: Extensions 1.2 (Contiguity Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Ws	Binary	Inverse_dist	Pop	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.609**	0.956***	0.360*	1.080***	0.615***	0.446**	0.597**	0.602***	0.625***	0.620***
	(0.237)	(0.290)	(0.186)	(0.385)	(0.234)	(0.200)	(0.243)	(0.229)	(0.233)	(0.220)
γ'	0.468	0.699	0.963	-0.573	0.462	0.778	0.380	0.478	0.411	0.428
	(0.713)	(0.694)	(0.640)	(1.215)	(0.716)	(0.630)	(0.719)	(0.697)	(0.711)	(0.688)
Grants	0.035***	0.041***	0.036***	0.051***	0.035***	0.034***	0.037***	0.035***	0.035***	0.035***
	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
l_income	0.002	0.003*	0.001	0.003*	0.002	0.002	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	1.110	0.580	1.471	1.250	1.125	1.080	1.199	1.054	1.086	0.995
	(1.731)	(1.746)	(1.688)	(1.839)	(1.744)	(1.684)	(1.725)	(1.720)	(1.738)	(1.728)
l_above 65	2.297	1.272	2.184	1.516	2.294	1.695	2.692*	2.183	2.394	2.415
	(1.478)	(1.402)	(1.448)	(1.527)	(1.489)	(1.409)	(1.518)	(1.455)	(1.486)	(1.472)
l_corruption	0.389	0.836	0.388	1.199	0.397	0.401	0.449	0.379	0.405	0.439
	(0.888)	(0.885)	(0.870)	(0.913)	(0.896)	(0.858)	(0.885)	(0.881)	(0.891)	(0.884)
l_manufacture	1.440**	1.598**	1.449**	2.104***	1.430**	1.396**	1.478**	1.460**	1.476**	1.479**
	(0.692)	(0.691)	(0.677)	(0.789)	(0.700)	(0.665)	(0.689)	(0.687)	(0.694)	(0.688)
l_infrastructure	1.597	1.388	1.487	2.173	1.664	1.649	1.420	1.542	1.580	1.463
	(1.478)	(1.485)	(1.463)	(1.458)	(1.494)	(1.418)	(1.465)	(1.462)	(1.479)	(1.462)
l_tax revenue	-0.292	-0.787	-0.259	-0.506	-0.277	-0.237	-0.259	-0.316	-0.281	-0.316
	(0.790)	(0.821)	(0.776)	(0.856)	(0.796)	(0.761)	(0.788)	(0.785)	(0.793)	(0.788)
l_sales tax rate	-210.228	-132.502	-158.165	-289.774	-216.571	-187.971	-224.519	-200.763	-219.261	-210.515
	(203.904)	(198.672)	(204.546)	(225.290)	(204.705)	(189.366)	(206.849)	(202.048)	(204.192)	(203.161)
l_corporate_ rate	39.711	69.520	23.324	100.640	45.987	59.380	30.635	34.984	39.848	41.740
	(78.396)	(78.115)	(77.487)	(81.019)	(79.331)	(75.266)	(78.091)	(77.655)	(78.708)	(78.053)
l_personal_rate	-87.073	-83.432	-16.578	-205.209	-92.997	-58.136	-100.952	-83.352	-98.315	-102.770
	(116.184)	(112.659)	(109.452)	(133.679)	(116.994)	(105.497)	(119.477)	(114.377)	(116.898)	(116.303)
Ajusted R Square	0.401	0.430	0.418	0.320	0.391	0.441	0.402	0.411	0.396	0.404

Table 3.9: Extensions 1.2 (Euclidean Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Euclidean Ws	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.790**	0.705*	0.833**	0.773**	0.733**	0.848**	0.513
	(0.305)	(0.381)	(0.324)	(0.344)	(0.318)	(0.427)	(0.348)
γ'	-0.097	-0.060	-0.208	0.350	-0.089	0.009	0.851
	(0.631)	(1.092)	(0.922)	(0.756)	(0.829)	(0.878)	(0.702)
Grants	0.049***	0.050***	0.051***	0.048***	0.050***	0.051***	0.051***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
l_income	0.003*	0.002	0.002	0.002	0.003*	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	1.976	1.990	1.802	2.050	1.636	1.526	1.714
	(1.781)	(1.772)	(1.801)	(1.841)	(1.833)	(1.864)	(1.811)
l_above 65	1.385	1.579	1.603	1.692	1.417	1.766	1.808
	(1.506)	(1.481)	(1.506)	(1.554)	(1.508)	(1.523)	(1.498)
l_corruption	1.183	1.110	1.108	1.115	1.311	1.121	1.068
	(0.901)	(0.896)	(0.901)	(0.930)	(0.901)	(0.912)	(0.898)
l_manufacture	1.945***	1.841**	1.958***	1.415*	1.881**	1.911***	1.626**
	(0.734)	(0.774)	(0.743)	(0.740)	(0.729)	(0.728)	(0.727)
l_infrastructure	1.985	2.097	2.228	1.929	2.400*	2.188	1.934
	(1.446)	(1.461)	(1.440)	(1.499)	(1.446)	(1.451)	(1.449)
l_tax revenue	-0.313	-0.241	-0.210	0.182	-0.301	-0.079	-0.189
	(0.839)	(0.840)	(0.839)	(0.832)	(0.864)	(0.837)	(0.836)
l_sales tax rate	-282.647	-263.101	-277.051	-291.532	-250.015	-276.274	-190.785
	(203.503)	(217.805)	(213.111)	(210.028)	(211.109)	(208.062)	(202.877)
l_corporate_ rate	112.482	101.118	89.376	133.889	101.008	83.088	86.491
	(79.960)	(79.640)	(79.663)	(84.916)	(80.524)	(80.691)	(79.237)
l_personal_rate	-153.252	-154.379	-158.439	-134.352	-155.888	-139.854	-66.317
	(105.375)	(128.273)	(113.225)	(112.326)	(112.613)	(114.293)	(107.655)
Ajusted R Square	0.340	0.358	0.337	0.292	0.339	0.319	0.343

Table 3.10: Extensions 2.1 (Contiguity Ws)

`	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Ws	Binary	Inverse_dist	Pop	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.724***	1.185***	0.537***	1.461	0.734***	0.581***	0.691***	0.711***	0.725***	0.705***
	(0.208)	(0.417)	(0.178)	(2.164)	(0.207)	(0.194)	(0.202)	(0.204)	(0.204)	(0.196)
Grants	0.037***	0.048***	0.041***	0.052***	0.037***	0.037***	0.038***	0.036***	0.036***	0.037***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
l_income	0.002	0.003*	0.002	0.003	0.002	0.001	0.002	0.002	0.002	0.002
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	1.112	0.167	1.552	0.939	1.052	1.358	1.223	1.091	1.089	1.092
	(1.877)	(2.081)	(1.912)	(1.899)	(1.894)	(1.919)	(1.829)	(1.876)	(1.870)	(1.862)
l_above 65	2.483	0.847	2.481	1.342	2.392	2.255	2.922*	2.387	2.560	2.693*
	(1.610)	(1.705)	(1.631)	(1.532)	(1.622)	(1.611)	(1.617)	(1.593)	(1.613)	(1.621)
l_corruption	0.503	1.346	0.615	0.957	0.544	0.468	0.528	0.484	0.507	0.509
	(0.940)	(0.956)	(0.944)	(1.417)	(0.942)	(0.982)	(0.926)	(0.936)	(0.940)	(0.942)
l_manufacture	1.580**	2.030***	1.758**	1.741	1.605**	1.510**	1.573**	1.595**	1.601**	1.569**
	(0.726)	(0.741)	(0.736)	(1.176)	(0.731)	(0.746)	(0.715)	(0.720)	(0.725)	(0.722)
l_infrastructure	1.957	2.124	2.426*	2.079	2.040	2.263	1.674	1.901	1.883	1.755
	(1.432)	(1.438)	(1.461)	(1.498)	(1.436)	(1.432)	(1.438)	(1.422)	(1.433)	(1.433)
l_tax revenue	-0.227	-1.082	-0.091	-0.584	-0.271	0.131	-0.188	-0.223	-0.220	-0.166
	(0.917)	(1.099)	(0.906)	(0.942)	(0.923)	(0.979)	(0.879)	(0.924)	(0.915)	(0.921)
l_sales tax rate	-268.227	-181.825	-289.047	-160.741	-270.170	-266.038	-274.993	-260.352	-270.964	-267.265
	(196.414)	(200.183)	(203.216)	(321.110)	(197.591)	(197.106)	(195.246)	(194.865)	(196.142)	(195.572)
l_corporate_ rate	49.707	93.070	48.031	113.559	56.006	87.049	37.241	45.045	48.502	52.838
	(80.595)	(79.990)	(82.578)	(106.275)	(80.679)	(81.524)	(80.351)	(80.367)	(80.476)	(80.045)
l_personal_rate	-138.158	-164.800*	-120.400	-159.593*	-142.950	-140.088	-144.785	-135.680	-143.495	-151.369*
	(89.738)	(91.254)	(92.437)	(92.705)	(90.223)	(90.178)	(89.490)	(89.014)	(89.708)	(89.591)
δ	-0.129	-0.828	-0.129	-2.083	-0.314	0.541	-0.024	-0.043	-0.128	0.119
	(1.237)	(1.373)	(0.958)	(9.004)	(1.237)	(1.560)	(1.098)	(1.261)	(1.250)	(1.299)
election year	2.808	8.354	1.632	34.392	5.468	-6.404	0.969	1.456	2.925	-0.535
	(18.627)	(20.022)	(15.648)	(168.551)	(18.621)	(21.896)	(17.626)	(18.789)	(18.776)	(19.386)
Ajusted R Square	0.343	0.333	0.311	0.319	0.337	0.337	0.350	0.353	0.344	0.347

Table 3.11: Extensions 2.1 (Euclidean Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Euclidean Ws	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.583	1.667*	1.346	-0.081	1.208	1.036	1.176
	(0.636)	(0.937)	(1.013)	(0.648)	(0.746)	(1.228)	(0.904)
Grants	0.052***	0.047***	0.052***	0.052***	0.053***	0.053***	0.051***
	(0.011)	(0.012)	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)
l_income	0.003*	0.002	0.002	0.002	0.002	0.002	0.003*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
l_jobless rate	1.654	1.656	1.390	1.257	1.134	1.214	1.101
	(1.827)	(1.936)	(1.880)	(2.107)	(1.896)	(1.927)	(2.022)
l_above 65	1.177	1.935	1.593	2.322	1.402	1.608	1.752
	(1.544)	(1.666)	(1.546)	(1.796)	(1.547)	(1.557)	(1.533)
l_corruption	1.365	0.786	0.822	1.661	1.061	1.083	0.915
	(1.020)	(1.012)	(1.067)	(1.082)	(1.015)	(1.053)	(1.052)
l_manufacture	2.040***	1.513*	1.792**	1.973**	1.681**	1.903**	1.761**
	(0.766)	(0.800)	(0.741)	(0.871)	(0.765)	(0.751)	(0.785)
l_infrastructure	2.162	1.772	2.117	1.550	2.530*	2.306	2.255
	(1.487)	(1.575)	(1.477)	(1.692)	(1.446)	(1.472)	(1.466)
l_tax revenue	-0.542	-0.311	-0.317	-0.298	-0.453	-0.265	-0.511
	(0.891)	(0.923)	(0.865)	(0.970)	(0.892)	(0.892)	(0.943)
l_sales tax rate	-270.751	-130.276	-193.407	-378.977	-132.670	-241.864	-166.542
	(205.165)	(232.543)	(217.029)	(233.003)	(236.829)	(224.979)	(242.387)
l_corporate_ rate	111.210	105.808	103.584	82.767	110.592	90.203	94.397
	(80.250)	(85.069)	(84.850)	(99.911)	(81.894)	(93.104)	(81.258)
l_personal_rate	-149.751*	-131.820	-145.321	-152.082	-138.481	-144.032	-142.520
	(90.851)	(98.545)	(91.790)	(105.630)	(94.414)	(91.468)	(91.713)
δ	0.785	-3.689	-2.242	3.466*	-1.458	-0.589	-1.416
	(2.376)	(3.381)	(4.010)	(2.031)	(2.200)	(4.192)	(2.783)
election year	-20.919	66.076	38.224	-70.634*	24.022	6.300	22.570
	(48.915)	(64.681)	(75.804)	(39.391)	(44.527)	(78.376)	(54.580)
Ajusted R Square	0.333	0.246	0.316	0.117	0.322	0.321	0.317

Table 3.12: Extensions 2.2 (Contiguity Ws)

`	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Ws	Binary	Inverse_dist	Pop	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.717***	0.995***	0.539***	0.999***	0.713***	0.596***	0.696***	0.708***	0.713***	0.707***
	(0.196)	(0.313)	(0.170)	(0.296)	(0.197)	(0.182)	(0.189)	(0.191)	(0.193)	(0.184)
Grants	0.034***	0.047***	0.039***	0.050***	0.035***	0.035***	0.035***	0.034***	0.034***	0.034***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
l_income	0.002	0.003*	0.002	0.003*	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	0.962	0.851	1.407	1.261	0.973	1.051	1.064	0.905	0.954	0.904
	(1.813)	(1.855)	(1.850)	(1.818)	(1.826)	(1.811)	(1.789)	(1.804)	(1.809)	(1.795)
l_above 65	2.099	1.331	2.269	1.345	2.113	1.783	2.352	2.017	2.149	2.139
	(1.503)	(1.515)	(1.552)	(1.518)	(1.513)	(1.486)	(1.501)	(1.489)	(1.502)	(1.492)
l_corruption	0.558	1.109	0.627	1.110	0.558	0.664	0.611	0.535	0.566	0.611
	(0.906)	(0.902)	(0.933)	(0.905)	(0.912)	(0.899)	(0.896)	(0.899)	(0.904)	(0.895)
l_manufacture	1.640**	1.859***	1.792**	1.825**	1.631**	1.660**	1.658**	1.661**	1.658**	1.661**
	(0.689)	(0.690)	(0.708)	(0.706)	(0.694)	(0.685)	(0.683)	(0.683)	(0.687)	(0.682)
l_infrastructure	1.911	2.026	2.335	1.944	1.976	2.229	1.694	1.830	1.852	1.757
	(1.417)	(1.423)	(1.450)	(1.438)	(1.424)	(1.402)	(1.413)	(1.409)	(1.416)	(1.408)
l_tax revenue	-0.466	-0.640	-0.280	-0.506	-0.445	-0.276	-0.470	-0.485	-0.454	-0.465
	(0.835)	(0.867)	(0.853)	(0.850)	(0.840)	(0.820)	(0.826)	(0.830)	(0.831)	(0.823)
l_sales tax rate	-264.337	-212.883	-295.612	-225.313	-268.075	-264.760	-268.770	-258.860	-265.795	-255.224
	(193.692)	(195.529)	(199.625)	(197.425)	(194.978)	(192.609)	(191.976)	(192.173)	(193.284)	(191.999)
l_corporate_ rate	53.985	98.040	55.533	102.426	60.809	82.865	42.645	48.723	52.879	54.356
	(79.806)	(79.330)	(82.329)	(79.923)	(80.100)	(78.614)	(79.610)	(79.388)	(79.673)	(79.022)
l_personal_rate	-141.864	-161.583*	-130.026	-155.473*	-146.668	-141.835	-145.231	-141.592	-145.986	-151.079*
	(89.335)	(90.301)	(91.968)	(91.524)	(89.992)	(88.851)	(88.604)	(88.627)	(89.199)	(88.660)
δ'	-0.633*	-0.105	-0.476	-0.485	-0.610	-0.529	-0.612*	-0.628	-0.623*	-0.615*
	(0.376)	(0.322)	(0.359)	(0.729)	(0.380)	(0.369)	(0.325)	(0.388)	(0.369)	(0.354)
election year	5.693	-1.071	3.483	4.920	5.365	4.022	5.461	5.534	5.566	5.485
	(7.552)	(6.966)	(7.451)	(13.242)	(7.625)	(7.377)	(7.201)	(7.549)	(7.479)	(7.328)
Ajusted R Square	0.351	0.344	0.312	0.336	0.343	0.359	0.363	0.361	0.354	0.363

Table 3.13: Extensions 2.2 (Euclidean Ws)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Euclidean Ws	Income	MedianHH	Corruption	Manufacture	Infrastructure	Edu	Higher edu
Neighbor's EDI	0.800***	0.710**	0.837***	0.858**	0.751**	0.947**	0.711**
	(0.299)	(0.311)	(0.320)	(0.346)	(0.327)	(0.378)	(0.349)
Grants	0.048***	0.049***	0.050***	0.046***	0.050***	0.050***	0.050***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
l_income	0.002	0.002	0.002	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
l_jobless rate	2.035	2.098	1.822	2.357	1.691	1.545	1.795
	(1.774)	(1.766)	(1.791)	(1.818)	(1.819)	(1.860)	(1.814)
l_above 65	1.267	1.508	1.460	1.487	1.264	1.620	1.784
	(1.513)	(1.481)	(1.508)	(1.545)	(1.519)	(1.532)	(1.507)
l_corruption	1.105	1.057	1.013	1.269	1.246	1.085	1.099
	(0.900)	(0.888)	(0.901)	(0.934)	(0.904)	(0.919)	(0.902)
l_manufacture	1.777**	1.735**	1.809***	1.404*	1.750**	1.807**	1.857***
	(0.704)	(0.692)	(0.696)	(0.735)	(0.701)	(0.708)	(0.702)
l_infrastructure	1.798	1.972	2.043	2.056	2.259	1.987	2.204
	(1.449)	(1.420)	(1.431)	(1.472)	(1.423)	(1.463)	(1.435)
l_tax revenue	-0.281	-0.232	-0.252	0.325	-0.276	-0.085	-0.144
	(0.836)	(0.833)	(0.833)	(0.829)	(0.852)	(0.839)	(0.838)
l_sales tax rate	-264.100	-248.965	-245.979	-282.612	-228.302	-255.888	-252.936
	(195.198)	(192.885)	(195.863)	(201.274)	(196.556)	(199.756)	(196.606)
l_corporate_ rate	117.408	105.494	96.220	143.595*	109.511	91.190	93.352
	(79.803)	(78.422)	(79.549)	(83.924)	(80.011)	(81.181)	(79.713)
l_personal_rate	-141.106	-147.251	-141.212	-142.276	-144.833	-134.302	-137.820
	(90.398)	(89.462)	(90.523)	(93.302)	(90.735)	(92.299)	(90.662)
δ'	-0.430	-0.409	-0.468	-0.904*	-0.510	-0.826	-0.224
	(0.562)	(0.690)	(0.671)	(0.490)	(0.665)	(0.763)	(0.737)
election year	4.168	3.188	3.950	11.414	5.424	10.379	1.115
	(11.270)	(12.405)	(12.715)	(10.155)	(12.786)	(14.051)	(13.158)
Ajusted R Square	0.344	0.361	0.343	0.303	0.342	0.316	0.340

Chapter 4: Economic Development Incentives and Income Inequality: Preliminary Analysis of US States

4.1 Introduction

This paper explores the relationship between the practice of offering economic development incentives (EDIs) and income inequality in U.S. states. Government policy makers use EDIs to influence business decisions so as to create a positive net benefit for the jurisdiction. Benefits can be direct and induced in the form of jobs, income, and state revenues. EDIs come in many forms, including grants, tax exemptions, tax refunds, tax credits, infrastructure investments, and even cash. No matter the type, EDIs lower a firm's cost of conducting business in a particular location. In so doing, EDIs redistribute public funds to private firms.

There is an increasing awareness by the popular press, watch dog organizations, and policy think tanks about the profligate use of EDI deals. Skepticism about the efficacy of EDI programs is supported by the academic literature which offers conflicting conclusions regarding EDI impacts on economic outcomes. The cost-benefit assessment is complex. It is difficult to pin down how much of an incentive is needed to close the gap between competing jurisdictions: communities lack information about the targeted firm's expected tax revenue and budget impacts, as well as the value of competitor's bids (which are not disclosed).

Firms have been successful in negotiating increasingly large EDI deals, often by initiating competitive bidding among jurisdictions. The more valuable the firm in terms of expected economic benefits, the more the competition, and the bigger the incentive needed to close the gap between competitors (Ellis and Rogers 2000). In the aggregate, state and local governments spend billions of dollars on EDIs. Large corporations have been successful at negotiating multi-million and even billion dollar deals. It is estimated that at least 75 percent of cumulative disclosed EDI dollars have gone to just 965 large corporations, even though these companies account for only about 10 percent of the number of announced awards.[45]According to another report from Good Jobs First (GJF), 99 firms have been awarded more than $19 billion in cumulative subsidies.[46] In fact, the GJF report argues that EDI awards to large corporations contribute to the increasing income inequality in the US. Notably, as they point out, many of the incentivized companies are well-known low-wage employers. The distributional impacts, however, are complex. For example low wage jobs may provide opportunities for unemployed workers, thereby increasing overall employment while adding more low wage earners to the income distribution. Furthermore, some high wage employers receive EDI as well

EDI have two potential impacts on the income distribution, beyond changing the mix of employers. First is the immediate impact of redistributing large amounts of public funds to private entities receiving the EDI. Second, EDI divert funds from other possible uses, including offering EDIs to other businesses, spending on public goods, and keeping tax rates low. Wang (2015) finds a negative relationship between EDI spending and investment in some public goods categories. To the extent that other spending leads to income enhancement opportunities, EDIs could negatively influence

[45] Subsidizing the Corporate One Percent: Subsidy Tracker 2.0 Reveals Big-Business Dominance of State and Local Development Incentives, by Philip Mattera (February 2014): http://www.goodjobsfirst.org/sites/default/files/docs/pdf/subsidizingthecorporateonepercent.pdf.

[46] Tax Breaks and Inequality: Enriching Billionaires and Low-Road Employers in the Name of Economic Development, by Philip Mattera, Kasia Tarczynska and Greg LeRoy (December 2014): http://www.goodjobsfirst.org/sites/default/files/docs/pdf/taxbreaksandinequality.pdf .

income equality, especially given that the largest corporations receive the biggest EDIs due to the intensity of the EDI competition.

Third, this research investigates the use of EDIs at the state level to identify the extent to which the use of EDIs is related with income inequality. The empirical analysis uses state level data on incentives and measures of income inequality. This preliminary investigation considers the relationship between subsidy values across states and inequality using the Subsidy Tracker data following Wang (2015) and income inequality using several common inequality measures following (Frank, 2009). The initial empirical specification builds on Wang (2015) using panel data methods. The results estimate the extent to which the practice of offering EDI is related to income inequality US states.

4.2 Relevant Literature

The literature on the efficacy of EDIs is both large and inconclusive. Please refer to Peters and Fisher (2004), Patrick (2012), and Wang (2014) for overviews. Rising income inequality over the past thirty years has been well documented in the literature (Williams, 2014; Leight, 2010; Frank, 2009). The literature regarding the relationship between income inequality and growth both within US and across countries is extensive (Leight, 2010).

Using data from 15 OECD countries during the period 2004 to 2012, Royuela et al (2014) find inequality is negatively associated with economic growth with the magnitude increases with city size. Frank (2009) mainly attributes the long term positive association between inequality (measured by top 10% income share) and growth at the state level to the concentration of income in the upper end of the income distribution. Using a Gini coefficient as an inequality measure, Leight (2010) finds that inequality has a significant and negative impact on growth in the short run in U.S. states. Further, he find that politics, growth and inequality are interlinked: growth increases and inequality decreases under Democratic control, compared with the opposite effects under Republican control.

In a related vein, Chintrakarn et al (2012) investigate the effect of Foreign Direct Investment (FDI) on income inequality in the US during 1977-2001 using panel cointegration techniques. They find the effect to be negative in the long term. However, this relationship differs across states: almost half of the 48 states exhibit a positive correlation between FDI and inequality.

Regarding the determinants of income inequality, Roine et al (2009) point out that increases in the top 1% income share which are associated with high growth comes at the expense of the rest of the top 10%. Further, government spending is found to increase the bottom 90% income share, decrease the income share of the upper middle class, while does not seem to affect the top percentile. Dincer and Gunalp (2012) emphasize the role of corruption and find that corruption is positively associated with income inequality in US states.

In addition to the relationship between inequality and growth, a number of studies focus on the effect of inequality on crime in the US. Brush (2007) finds income inequality and crime rates are positively correlated using cross-section analysis whereas the relationship is negative under time-series analysis. Choe (2008) shows that income inequality has strong and robust effects on burglary and robbery crimes, but fails to find evidence relating inequality to other categories of crime. In contrast to prior research, Chintrakarn and Herzer (2012) find that income inequality reduces crime, possibly due to increased protection against crimes.

To summarize, the literature covers a host of related mechanisms by which government policy influences inequality. However, the link between EDI spending decisions and inequality impacts has not been investigated heretofore. The estimation that follows addresses this gap: are EDI expenditures related to inequality measures at the state level?

4.3 Model Specification and Estimation

4.3.1 Baseline Model

Following Dincer and Gunalp (2012), a dynamic panel model is adopted to analyze the effect of EDIs on income inequality. The baseline estimation is as follows:

[1] $y_{it} = \alpha y_{it-1} + \beta EDI_{it} + \gamma' X_{it} + \delta_i + \mu_t + \nu_{it}$,

where the dependent variable y_{it} is the income inequality measure in state i year t. The parameter of interest, β, is the coefficient corresponding to EDI spending in state i year t. X_{it} is a vector of conditioning variables (including an intercept) that are thought to influence income inequality. State and year fixed effects (δ_i and μ_t) account for state level characteristics that do not change over time and macroeconomic shocks that affect all states at the same time.

Inclusion the lagged dependent variable creates estimation challenges. To better see this, Equation [1] is written in a more generic form:

[2] $y_{it} = \alpha y_{it-1} + \beta' X_{it} + \varepsilon_{it}$,

$\varepsilon_{it} = \delta_i + \mu_t + \nu_{it}$, for $i = 1, 2, \ldots, N$, $t = 2, \ldots, T$.

We can easily tell that lagged dependent variable y_{it-1} is correlated with δ_{i} in the error term. This endogeneity causes OLS estimator to be biased and inconsistent. Further, this problem cannot be circumvented with 2SLS or panel fixed effects estimator (Roodman, 2009). The Generalized Method of Moments (GMM) estimator proposed by Arellano and Bond (1991) is a standard way to address these concerns (Roine et al, 2009).

4.3.2 GMM Estimator: Arellano and Bond (1991)

The GMM estimator starts with first differencing the model to remove state fixed effects. The transformed model is estimated using lagged levels of the dependent variable and endogenous variables, as well as differences of exogenous variables as instruments. The first differenced model and moment conditions are listed as below.

[3] $\Delta y_{it} = \alpha \Delta y_{it-1} + \beta' \Delta x_{it} + \Delta \varepsilon_{it}$,

$\Delta \varepsilon_{it} = (\delta_{i} - \delta_{i}) + \Delta \mu_t + \Delta \nu_{it}$, for i = 1, 2,…, N and t = 2,…,T ,

[4] E ($y_{it-s} \Delta \varepsilon_{it}$) = 0 for t = 3, 4,…, T and s > = 2.

[5] E ($\Delta x_{it-s} \Delta \varepsilon_{it}$) = 0 for t = 3, 4,…, T and s >= 2.

First differencing, however, shrinks the data set and amplifies gaps in an unbalanced panel. If y_{it} is missing, for example, then both Δy_{it} and Δy_{it+1} are missing in the first differenced transformed data. Alternative transformations, forward orthogonal deviations or orthogonal deviations, helps to mitigate the problem (Arellano and Bover 1995). In contrast to the first differencing transformation, which deducts observation from last period from the present one, the forward orthogonal deviation transformation subtracts the average of all future values from the present one (Roodman, 2009). Thus, the forward orthogonal deviation transformation only discards the last observation for each group, which minimizes data loss.[47] I adopt the forward orthogonal deviation transformation as a robustness check.

Lagged independent variables can be poor instruments when they do not change much over time, which is a potential problem with difference GMM estimator. This does not seem to be a problem for my estimation. Nevertheless, a third robustness estimates the baseline model through dynamic system GMM, developed by Blundell and Bond (1998). It helps to address the aforementioned problem with difference GMM by providing more moment conditions available from the level equation. Following Blundell and Bond (1998) the level equation [2] is incorporated in the first-differenced GMM. Variables in the level equation are instrumented with their own differences.

4.3.3 Specification Tests for GMM Estimators: AR (1), AR (2) and Sargan/Hansen Tests

The consistency of the difference GMM estimator depends critically on the validity of the moment conditions listed in [4] – [5] and the lack of second order serial correlation in the error terms. The Sargan/Hansen test is used to examine the validity of instruments. The null hypothesis is that the instruments are exogenous as a group. As a result, a higher p-value of the Sargan/Hansen statistic is preferred.

The other important diagnostic is the AR test for autocorrelation of the residuals. The consistency of the GMM estimator relies on the lack of second order serial correlation. By construction, the residuals of the first differenced equation should possess serial correlation. Accordingly, the null is always rejected for the AR (1) test. For instruments to be valid, differenced residuals should not show significant second

[47] Further, Hayakawa (2009) shows in a recent simulation study that the GMM estimator transformed by forward orthogonal deviation tends to perform better than the one transformed by first differencing.

order of serial correlation. Accordingly, a high reported p-value in AR (2) test indicates that the moment conditions are valid. If the AR (2) statistic is significant, longer lags need to be used.

The other important diagnostic is the AR test for autocorrelation of the residuals. The consistency of the GMM estimator relies on the lack of second order serial correlation. By construction, the residuals of the first differenced equation should possess serial correlation. Accordingly, the null is always rejected for the AR (1) test. For instruments to be valid, differenced residuals should not show significant second order of serial correlation. Accordingly, a high reported p-value in AR (2) test indicates that the moment conditions are valid. If the AR (2) statistic is significant, longer lags need to be used.

4.4 Data

To measure income inequality, I rely on the measures constructed by Mark Frank who created measures for a panel of 50 states plus DC spanning 1917 to 2012 using individual tax filing data available from the Internal Revenue Service[48] Three inequality measures are employed in this paper: Top 1%, Top 10%, and Gini Coefficient. The first two measure the concentration of income at the top level whereas the Gini Coefficient summarizes the entire income distribution.

The control variables largely follow the work of Dincer and Gunalp (2012). Economic variables include personal income, top statutory state corporate income tax rate, top statutory personal income tax rate, unemployment rate, manufacturing share of

[48] U.S. State-Level Income Inequality Data - Mark W. Frank: http://www.shsu.edu/eco_mwf/inequality.html. The IRS data report gross income that includes the following: wages and salaries, capital income (dividends, interest, rents, and royalties) and entrepreneurial income (self-employment, small businesses, and partnerships).

employment, government spending on welfare programs. Demographic characteristics include percentage of young population, percentage of old population, and years of education. Political variables include union membership, corruption, as well as bipartisanship at the state level. Table 4.1 provides variable descriptions and data sources. Government finance data (public welfare spending and unemployment compensation), manufacturing share of employment and demographic characteristics are obtained from US Census, while personal income and unemployment rates are from the Bureau of Economic Analysis (BEA). Top statutory state corporate income tax rate and top statutory state personal income tax rate data are collected from Tax Foundation and Tax Policy Center respectively. The U.S. Department of Justice provides reports of federal public corruption convictions. Union membership data, measured by percentage of nonagricultural employees covered by a collective bargaining, are made available by Hirsch[49] 'Democratic control' is a dummy variable which equals 1 if both the state governor and legislature belong to the Democratic Party based on data provided by the National Governor Association (NGA) and National Conference of State Legislatures (NCSL).

The sample data includes control variables and EDI data. All dollar figures are transformed to a per capita basis and deflated using CPI with 1982-1984 as the base year. Data availability restricts the sample to 43 states over the period 2000-2009. The dataset contains 340 observations. Examining the sample reveals that per capita EDI spending ranges over the time period from less than a dollar (Louisiana in 2004) to $558 (New Mexico in 2004) with an average of $17 across all states and years. The income share of the top percentile are highest in New Mexico in 2000 (32%) and lowest

[49] His webpage contains state union membership data from 1983 to 2014: http://www.unionstats.com/.

in Connecticut in 2000 (15%) with an average of 19%. The manufacturing share of employment average is 12.10 percent, ranging from 4 to 24 percent. Corruption rate varies extensively with the average being 3.39 convictions per 1,000,000 residents. The highest occurred in North Dakota in 2003 (25 convictions) and the lowest was in Oregon in 2002 (0.28 convictions). The mean of union membership is 11.66% with New York in 2001 being the most unionized state (26.9%) and North Carolina in 2004 being the least unionized (2.8%). Colorado in 2009 was the most educated state with 14.44 years of education compared with an average of 13.6 years. Per capita expenditures on public welfare and unemployment compensation are small compared with other public expenditure categories. The averages are less than a dollar: New York in 2005 and New Jersey in 2009 spend the most on welfare and unemployment, $1.14 and $0.18 respectively. Table 4.2 provides summary statistics.[50]

4.5 Results

Table 4.3 through 4.6 shows OLS, Fixed Effect (FE), Difference GMM, and System GMM estimation results respectively. For OLS and FE estimation, columns [1] to [3] display estimated coefficients for equation [1] without lagged dependent variable, with lagged dependent variable, and further with one year lag of EDI respectively.[51]

The first column of Table 4.3 (OLS estimation) indicates that EDI spending and top 1% income shares are positively correlated. In addition, years of education, democratic control, manufacturing share of employment, top corporate and personal income tax rates are all negatively associated with top 1% income share. Further, the

[50] Top1, EDI, Public welfare_exp, Unemployment_exp, and Income are expressed in natural log forms. Income square is added to explore the nonlinear relationship between growth and inequality (Dincer and Gunalp, 2012; Kim, Huang and Lin, 2011; Ram, 1991).

[51] One year lag of EDI is included to account for lagged effect of EDI on income inequality.

positive coefficient on the income variable and negative coefficient on income squared are consistent with Kuznets' inverted-U hypothesis about the relationship between income inequality and growth, which states income inequality first worsens and then improves over the course of economic development. The estimated coefficients of one year lags of top percentile income share, shown in the last two columns, are highly statistically significant. In these specifications, only expenditures on unemployment compensation, unemployment rate, and percentage of population above 65 are statistically significant: they are negatively related to the income share of top percentile. For FE estimation in Table 4.4, we consistently confirm Kuznets' hypothesis and see the negative relationship between union membership and top one percent income share.

Difference GMM (Table 4.5) and System GMM (Table 4.6) results are similar in that both find evidence of EDI spending positively associated with the income share of top percentile, regardless of EDI spending is treated as exogenous or not.[52] Given both variables are in natural log forms, the coefficients can be interpreted as elasticities: a 1% increase in per capita EDI spending is correlated with a 0.008% to 0.021% increase in top percentile income share. In addition, years of education are also negatively associated with income inequality, consistent with findings of Dincer and Gunalp (2012). Kuznets' inverted-U hypothesis is again supported under difference GMM estimation, which is in line with previous studies (Kim, Huang, and Lin, 2011). There exists mixed evidence regarding the relationship between elder population and income equality with the estimates negative in most cases. Strangely, unemployment rate is positively related to the income share of top percentile.

[52] EDI spending is treated as exogenous in columns [1] and [3], endogenous in columns [2] and [4].

4.6 Conclusion and Extensions

This analysis investigates the relationship between EDI use and measures of income inequality at the state level. Drawing from data provided by GJF, the results suggest that EDI spending appears to be linked with widening income inequality, measured as top 1% share of income.

There are important caveats worth noting. EDI may impact other economic measures such as growth, investment, employment, etc. However, the cost of potential benefits in these aspects could be a widening of income inequality. Considering the equality implications of the use of EDIs programs is an important factor in evaluations of EDI policy decisions.

Data is another caveat. Although GJF is a national database and supports cross state analysis, it has limitations. These include aggregate reporting of multiple period EDI awards as well as the potential of missing observations of EDI programs, particularly smaller and less well publicized awards. To that end, analysis using different measures of EDIs, such as the database created by C2ER, would be a useful extension.

There are many avenues for expanding this analysis, including: (1) Using other measures of income inequality to explore the relationship between EDI spending and inequality; (2) Extending the sample to include the period before 2000; and (3) Performing robustness check using forward orthogonal deviation transformation. I leave these for future work.

Table 4.1: Variable Names and Data Sources

Variable	Description	Source
Top 1	Income share of the top 1%	http://www.shsu.edu/~eco_mwf/inequality.html
EDI	EDI spending ($)	Subsidy Tracker (GJF)
Public welfare_exp	Spending on Welfare Programs($)	U.S. Census
Unemployment_exp	Unemployment Compensation($)	U.S. Census
Yrs of Edu	Years of education	Turner et al (2006)
Income	Personal income ($)	Bureau of Economic Analysis (BEA)
Jobless Rate	Unemployment rate (%)	Bureau of Economic Analysis (BEA)
Union	% of nonagricultural employees covered by a collective bargaining	http://www.unionstats.com/
Above65	% of elder population	U.S. Census
Below15	% of young population	U.S. Census
Corruption	Convinctions per 1,000,000 residents	U.S. Department of Justice
Democratic control	Dummy variable equals 1 if state governor and legislature belong to the Democratic party	Calculated by author from NGA and NCSL
Corporate income tax rate	Top statutory corporate income tax rate (%)	Tax Foundation
Individual income tax rate	Top statutory personal income tax rate (%)	Tax Policy Center
Manufacturing	Manufacturing share of employment (%)	U.S. Census

Notes:

(1) I take natural log of the following variables: Top1, EDI, Public welfare_exp, Unemployment_exp, and Income.

(2) All dollar values are on a per capita basis and deflated by CPI (1982-84=100).

Table 4.2: Summary Statistics (n=340)

Variables	Mean	Std. Dev.	Min	Max
Top 1	2.93	0.18	2.48	3.42
EDI	1.37	1.90	-5.47	6.32
Public welfare_exp	-0.59	0.27	-1.37	0.13
Unemployment_exp	-2.96	0.55	-4.52	-1.70
Yrs of Edu	13.62	0.37	11.90	14.45
Income	9.78	0.14	9.43	10.20
Income^2	95.57	2.67	89.02	104.07
Jobless Rate	5.36	1.78	2.2	13.3
Union	11.66	5.50	2.8	26.9
Above65	12.66	1.58	7.57	17.52
Below15	20.41	1.43	16.80	26.79
Corruption	3.39	2.72	0	25.05
Democratic control	0.22	0.42	0	1
Corporate income tax rate	0.06	0.03	0	0.12
Individual income tax rate	0.05	0.03	0	0.12
Manufacturing	12.10	4.49	4.01	23.69

Notes: ‘Income^2 is the square of personal income in natural log form.

Table 4.3: OLS Estimation for Top 1

	[1]	[2]	[3]
Top 1 (t-1)		0.750***	0.748***
		(0.045)	(0.045)
EDI	0.008**	0.008*	0.007
	(0.003)	(0.004)	(0.005)
EDI (t-1)			0.001
			(0.005)
Public welfare_exp	0.042	0.038	0.037
	(0.039)	(0.032)	(0.032)
Unemployment_exp	0.027	-0.050**	-0.050**
	(0.025)	(0.021)	(0.021)
Yrs of Edu	-0.109***	-0.050*	-0.050*
	(0.020)	(0.026)	(0.026)
Income	19.795***	0.164	0.347
	(6.026)	(5.792)	(5.846)
Income^2	-0.990***	-0.009	-0.018
	(0.307)	(0.293)	(0.296)
Jobless Rate	0.007	-0.024***	-0.024***
	(0.006)	(0.005)	(0.005)
Union	-0.003	0.003*	0.003*
	(0.002)	(0.002)	(0.002)
Above 65	0.028***	-0.014**	-0.015**
	(0.006)	(0.006)	(0.006)
Below 15	0.036***	-0.011	-0.011
	(0.006)	(0.007)	(0.007)
Corruption	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Democratic control	-0.041***	-0.010	-0.010
	(0.013)	(0.014)	(0.015)
Corporate income tax rate	-0.484**	0.103	0.102
	(0.206)	(0.216)	(0.217)
Individual income tax rate	-0.570***	-0.240	-0.232
	(0.207)	(0.223)	(0.221)
Manufacturing	-0.009***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Constant	-95.494***	1.039	0.150
	(29.547)	(28.553)	(28.818)
# of Obs	340	281	281
Adj. R-Square	0.70	0.72	0.72

Table 4.4: FE Estimation for Top 1

	[1]	[2]	[3]
Top 1 (t-1)		0.476***	0.475***
		(0.046)	(0.047)
EDI	0.003	-0.001	-0.001
	(0.004)	(0.003)	(0.003)
EDI (t-1)			0.001
			(0.003)
Public welfare_exp	-0.098	0.127**	0.126**
	(0.080)	(0.063)	(0.063)
Unemployment_exp	0.028	-0.090***	-0.090***
	(0.032)	(0.024)	(0.024)
Yrs of Edu	-0.028	-0.022	-0.023
	(0.041)	(0.048)	(0.048)
Income	72.832***	32.079***	32.208***
	(9.037)	(8.502)	(8.538)
Income^2	-3.707***	-1.681***	-1.687***
	(0.459)	(0.434)	(0.436)
Jobless Rate	0.000	-0.041***	-0.041***
	(0.007)	(0.006)	(0.006)
Union	-0.013***	-0.016***	-0.016***
	(0.005)	(0.005)	(0.005)
Above 65	0.026	-0.197***	-0.197***
	(0.052)	(0.029)	(0.029)
Below 15	-0.042	-0.167***	-0.168***
	(0.031)	(0.022)	(0.022)
Corruption	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)
Democratic control	-0.006	-0.025*	-0.025*
	(0.015)	(0.015)	(0.015)
Corporate income tax rate	0.168	0.327	0.326
	(0.156)	(0.200)	(0.201)
Individual income tax rate	-0.124	-0.557	-0.551
	(0.197)	(0.401)	(0.402)
Manufacturing	-0.012	-0.035***	-0.035***
	(0.013)	(0.008)	(0.008)
Constant	-353.673***	-144.573***	-145.151***
	(43.889)	(41.400)	(41.562)
# of Obs	340	281	281
# of Groups	47	43	43
Adj. R-Square	0.85	0.85	0.85

Table 4.5: Difference GMM Estimation for Top 1[53]

	[1]	[2]	[3]	[4]
Top 1 (t-1)	0.687***	0.761***	0.688***	0.742***
	(0.042)	(0.055)	(0.044)	(0.056)
EDI	0.011**	0.021*	0.008**	0.019
	(0.004)	(0.012)	(0.004)	(0.012)
EDI (t-1)			0.002	-0.006
			(0.004)	(0.004)
Public welfare_exp	0.046	0.021	0.048	0.196
	(0.035)	(0.042)	(0.036)	(0.138)
Unemployment_exp	-0.058***	-0.025	-0.057***	-0.024
	(0.018)	(0.023)	(0.018)	(0.026)
Yrs of Edu	-0.052**	-0.054**	-0.052**	-0.073**
	(0.025)	(0.024)	(0.025)	(0.031)
Income	0.407***	0.451***	0.410***	0.482***
	(0.116)	(0.119)	(0.116)	(0.156)
Income^2	-0.021**	-0.024***	-0.021**	-0.024**
	(0.008)	(0.009)	(0.008)	(0.011)
Jobless Rate	-0.026***	-0.032***	-0.026***	-0.034***
	(0.005)	(0.005)	(0.005)	(0.007)
Union	0.003*	0.002	0.003*	0.000
	(0.002)	(0.002)	(0.002)	(0.003)
Above 65	-0.014*	-0.021***	-0.014*	-0.019**
	(0.008)	(0.008)	(0.007)	(0.010)
Below 15	-0.011	-0.016*	-0.010	-0.004
	(0.008)	(0.009)	(0.008)	(0.014)
Corruption	-0.004	-0.002	-0.004	-0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Democratic control	-0.001	-0.006	-0.001	-0.009
	(0.021)	(0.023)	(0.022)	(0.023)
Corporate income tax rate	0.111	0.279	0.104	0.151
	(0.199)	(0.200)	(0.199)	(0.227)
Individual income tax rate	-0.379	-0.326	-0.375	-0.768
	(0.311)	(0.315)	(0.313)	(0.527)
Manufacturing	-0.002	-0.003	-0.002	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)
# of Obs	281	281	281	281
# of Groups	43	43	43	43
AR(1)	0.00	0.01	0.00	0.02
AR(2)	0.71	0.42	0.72	0.51
Hansen Test	0.65	0.80	0.68	0.95

[53] EDI is treated as exogenous in columns [1] and [3], endogenous in columns [2] and [4], same for Table 4.6.

Table 4.6: System GMM Estimation for Top 1

	[1]	[2]	[3]	[4]
Top 1 (t-1)	0.687***	0.761***	0.688***	0.742***
	(0.042)	(0.055)	(0.044)	(0.056)
EDI	0.011**	0.021*	0.008**	0.019
	(0.004)	(0.012)	(0.004)	(0.012)
EDI (t-1)			0.002	-0.006
			(0.004)	(0.004)
Public welfare_exp	0.046	0.021	0.048	0.196
	(0.035)	(0.042)	(0.036)	(0.138)
Unemployment_exp	-0.058***	-0.025	-0.057***	-0.024
	(0.018)	(0.023)	(0.018)	(0.026)
Yrs of Edu	-0.052**	-0.054**	-0.052**	-0.073**
	(0.025)	(0.024)	(0.025)	(0.031)
Income	0.407***	0.451***	0.410***	0.482***
	(0.116)	(0.119)	(0.116)	(0.156)
Income^2	-0.021**	-0.024***	-0.021**	-0.024**
	(0.008)	(0.009)	(0.008)	(0.011)
Jobless Rate	-0.026***	-0.032***	-0.026***	-0.034***
	(0.005)	(0.005)	(0.005)	(0.007)
Union	0.003*	0.002	0.003*	0.000
	(0.002)	(0.002)	(0.002)	(0.003)
Above 65	-0.014*	-0.021***	-0.014*	-0.019**
	(0.008)	(0.008)	(0.007)	(0.010)
Below 15	-0.011	-0.016*	-0.010	-0.004
	(0.008)	(0.009)	(0.008)	(0.014)
Corruption	-0.004	-0.002	-0.004	-0.003
	(0.003)	(0.002)	(0.003)	(0.003)
Democratic control	-0.001	-0.006	-0.001	-0.009
	(0.021)	(0.023)	(0.022)	(0.023)
Corporate income tax rate	0.111	0.279	0.104	0.151
	(0.199)	(0.200)	(0.199)	(0.227)
Individual income tax rate	-0.379	-0.326	-0.375	-0.768
	(0.311)	(0.315)	(0.313)	(0.527)
Manufacturing	-0.002	-0.003	-0.002	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)
# of Obs	281	281	281	281
# of Groups	43	43	43	43
AR(1)	0.00	0.01	0.00	0.02
AR(2)	0.71	0.42	0.72	0.51
Hansen Test	0.65	0.80	0.68	0.95

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