Did Hate Crime Laws Help Decreasing Hate Crimes? Evidence from United States using Difference-in-Difference Analysis

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Work in Progress

1 Abstract

In this paper I present empirical evidence from United States to investigate the effectiveness of hate crime laws. Hate crime laws were progressively adopted on a state-basis. This research focuses on Virginia and Mississippi, which adopted hate crime laws in 1994. Difference-in-Difference is used to develop causal inferences. The treatment effect is significant on a $p<0.01$ level.

2 Introduction

Hate crime is a prejudice-motivated crime. It usually involves violence against a victim because of the victim's race, sexual orientation, gender identity, ethnicity, religion (Meyer, 2014). Unlike other crime, hate crime is particularly important to the society as it reflects the social norm and people's ideology.

Hate crime laws are laws that enhance penalty towards conducts that are already regarded as crimes in other laws. Hate crime laws have a long history in United States, the earliest one dates back to 1871, the Civil Rights Act of 1871, to fight against Ku Klux Klan. However, states have different hate crime laws. While each states have different state-level laws, it is possible to measure hate crime laws in a standardized manner.

In this research, two data sources were merged to form a panel data to conduct regressions. The first is a panel data that includes state policies adoptions, changes and pre-determined features (Jordan and Grossmann, 2016). The other one is the hate crime statistics provided by FBI Uniform Crime Reporting (FBI, 2012).

With the panel data, this research focuses on the effects of hate crime laws adoption using quantitative approach, specifically, Difference-in-Difference (DiD). The DiD shows that the two states (Virginia and Mississippi) that adopted hate crime laws in 1994 demonstrated a short-term decreasing effect on hate crime occurrence.

2.1 Literature Review

The literature has little to offer in terms of quantitative research on the topic of hate crime laws. Most dominant researches were conducted in other methods other than quantitative methods.

For example, "The Homogenization and Differentiation of Hate Crime Law in the United States, 1978 to 1995: Innovation and Diffusion in the Criminalization of Bigotry" (Grattet et al., 1998) analyze the characteristics of the legislation of hate crimes in a non-quantitative manner.

Thanks to the data that were not publicly available until recently, this research can utilize the data to look into this the hate crime laws adoption effect in a quantitative manner.

3 Data: The Correlates of State Policy Project & FBI Uniform Crime Reporting Database

The Correlates of State Policy Project (Jordan and Grossmann, 2016) provides a comprehensive approach to access the state hate crime law effectiveness. This panel data tracks the policy differences and change over time in the 50 states in the U.S from 1900 to 2016. It also includes pre-determined variable such as population and income; and policy outputs, such as State Policy Liberalism Score.

In the panel data, there are a handful of variables that are worth noticing. First, hate crime might be correlated to public opinion, partisanship and residents' political ideologies. For instance, Conservative Identifiers, which is an over time measure of the percent who identify as political conservatives in each state (Jordan and Grossmann, 2016). After careful selection and regression experiments, I found the following three variable that are most relevant (**Table 1**).

Variable Name	Description
conservative	Conservative Identifiers
edattendrate	Average School Attendance Rate
pc_inc_ann	Per Capital Annual Income

TABLE 1: Pre-determined Features included in χ .

These three pre-determined features represent three crucial aspects of the states: basic education, political ideology, and economics.

However, not every variable is available from 1990 - 2016. Many of the variables are only available for a limited period. State Hate Crime Laws (*hatecrime*) dummy variable only provided data from 1978 to 1994. Therefore, I selected a time frame of 1992 - 2000 where most variables are available.

In addition to the Correlates of State Policy Project, a hate crime database, Federal Bureau of Investigation (FBI)'s Uniform Crime Reporting (UCR) database (FBI, 2012), is used to provide hate crime statistics to measure the adoption outcome, i.e. the treatment effect. However, the hate crime statistics are only available from 1992 to 2012. For robustness reasons, I chose the Mississippi and Virginia as the treatment group, and the rest of the states that never adopted hate crime laws as control group.

For the sake of human readability, I compute the hate crime rate as the following:

$$\text{scaled hate crime rate}_{ij} = \frac{\text{hate crime occurance}_{ij}}{\text{population}_{ij}} \times 10^5 \tag{1}$$

That is, the variable *hc_rate10_5* measures the hate crime occurrence per 10^5 people within i^{th}state in year j.

Variable	Obs	Mean	Std. Dev.	Min	Max
hc_rate10_5	152	1.981658	2.184248	0.04	11.82797
hate_crime_count	134	51.58209	63.2532	1	330
conservative	152	32.48973	5.707531	11.52309	46.06831
pc_inc_ann	152	22656.86	4470.106	16135	40462
edattendrate	152	92.97986	3.539022	84.684	105.391

TABLE 2: Descriptive Statistics of Relevant Variables from 1992 to 2000

For comparison, *hate_crime_count* is the absolute occurrence of hate crime incidence. The states with missing hate crime statistics will be excluded from the regression.

4 Empirical Method

This study tries to conduct causality regarding the hate crime laws outcome. Not all states adopted hate crime laws at the same time. This situation makes Difference-in-Difference analysis great for this task.

One of the most important hate crime dummy variable,*hatecrime*. This dummy variable measures "Did State adopt State Hate Crime Laws?", where:

$$\text{hatecrime}_{ij} = \begin{cases} 1, & \text{if state } j \text{ had effective hate crime laws in year } i \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

First, I identify the law adoptions by tracking the dummy variable change for each state (**Table 4** In Appendix). And the adoption year in the **Table 4** is the year when the state's hatecrime dummy turned to 1. In total, 33 states were identified for hate crime law adoptions. The rest of the state did not adopt hate crime laws in the research time frame 1992 - 2000.

The main Difference-in-Difference regression is shown in **Equation 3**:

$$\text{hate crime rate}_{ij} = c + \text{treatment}_i + \text{post}_i + \text{treatment}_i \times \text{post}_j + \vec{\chi}_{ij} + \vec{\gamma}_j + \epsilon \tag{3}$$

where i represents the state and j represents year. *treatment* is a dummy variable for treatment group. It equals to 1 if the state is Mississippi and Virginia. *post* is the dummy variable that equals to 1 if the state is both in treatment group and after 1994. χ is a series of pre-determined features of each state in each year. γ is a series of year dummy variables, which capture the common trend across all states.

The reason to include the year dummy γ is to capture the overall common hate crime trend on a national level. While hate crime statistics were correlated with the national statistics, the national statistics and the state statistics were extremely volatile among years. Therefore, the year dummy could better capture the trend than *post* dummy variable.

5 Results

First, I examine the short term effect of hate crime laws. I ran the regression (**Equation 3**) on year 1992 to 1996, two years before treatment group's adoption of hate crime laws and two years after the adoption.

The regression result is shown in **Table 3**:

hc_rate10_5	Coefficient	Notes
treat	0.793	The treatment dummy
	(0.810)	
post	-1.569**	The post dummy
	(0.564)	
post_treat	-1.804***	The DiD estimator, treatment effect
	(0.572)	
1992.year	-1.679***	Year Dummy for 1992
	(0.404)	
1993.year	-0.878**	Year Dummy for 1993
	(0.335)	
1994.year	-1.550***	Year Dummy for 1994
	(0.485)	
1995.year	1.096***	Year Dummy for 1995
	(0.367)	
pc_inc_ann	1.01E-05	Per Capital Annual Income
	(9.23e-05)	
edattendrate	-0.0746	Average School Attendance Rate
	(0.0958)	
conservative	-0.267***	Conservative Identifiers
	(0.0421)	
Constant	18.79*	
	(9.862)	
Observations	90	
R-squared	0.533	
	*** p<0.01, ** p<0.05, * p<0.1	Clustered by States

TABLE 3: Regression (**Equation 3**) result from year 1992 - 1996.

The treatment effect, i.e. the effect of adopting the hate crime laws, is reflected in the coefficient of DiD Estimator(*post_treat*). Its coefficient is -1.804, which implies that the hate crime laws adoption could decrease the hate crime rate per 10^5 per year. The magnitude may seem insignificant, however, consider the value distribution of hate crime statistics of the treatment group (**Figure 1**):

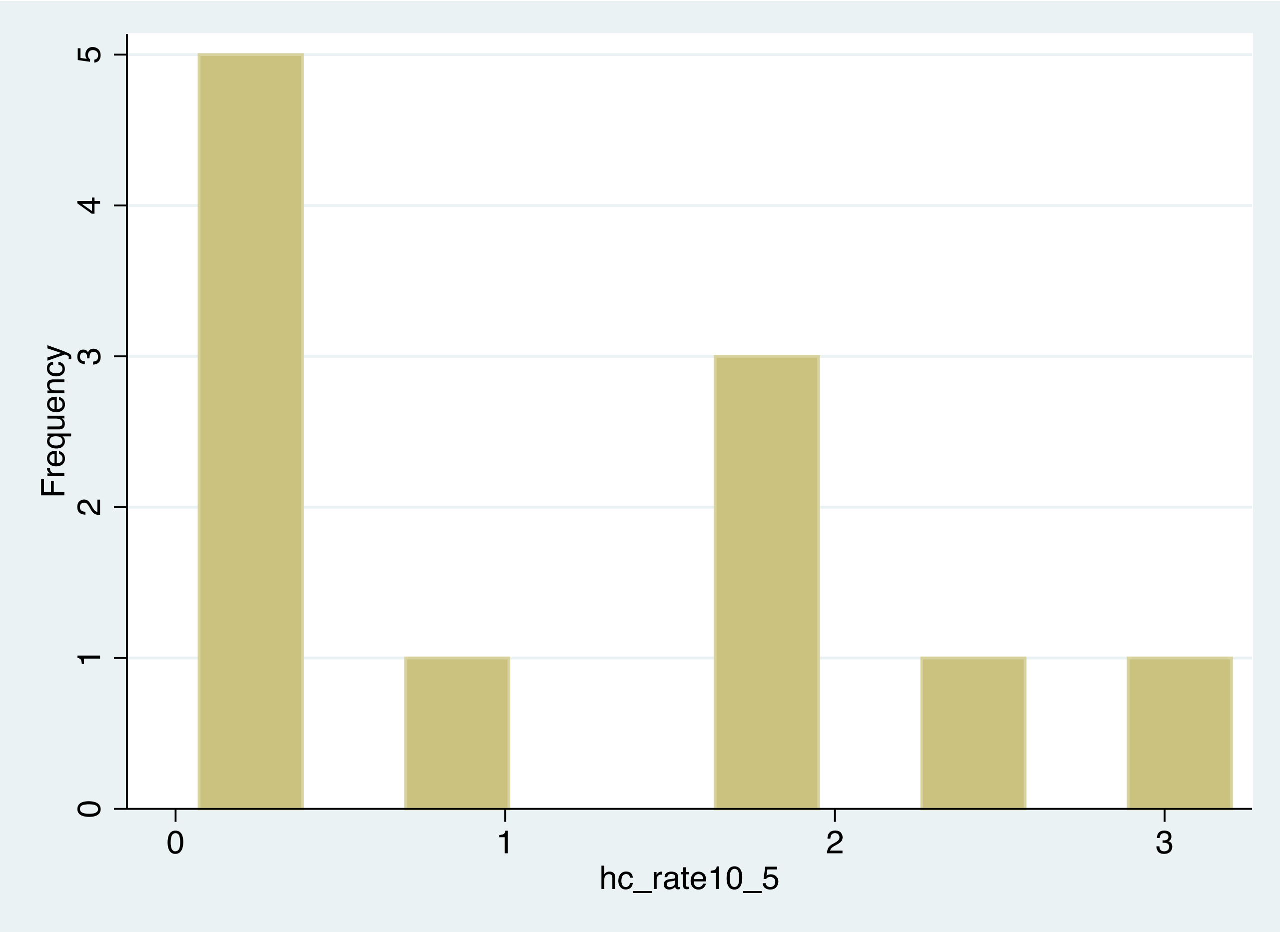

Figure 1: Hate Crime Rate Statistics Distribution of Treatment Group from 1994 to 2000.

For most years, a decrease of -1.8 means a significant decrease of at least 50%.

The following figure shows the trends of hate crime rates grouped by state hate crime laws adoption status.

In 1992 - 1994, the control group (red line) and the treatment group states (green line) followed a common trend. In 1995, after the treatment group (Mississippi and Virginia) adopted hate crime laws, the treatment group's hate crime statistics moved against the common trend shown by the control groups. Starting from 1995, the treatment group also moved against the common trend. After 1997, these groups were in sync with the common trend. However, in 1995 - 1998, the treatment was the reverse of the expected outcome.

If we extend post-adoption period in the regression to 1998, the treatment is still significant at a p=0.05 (0.033) level, where the coefficient becomes -1.2876, lower than previous value -1.804. If the window is further extended to 1992 - 2000, the treatment effect becomes insignificant.

The results of this two regressions are shown in **Table 4** and **Table 5**, which can be found in Appendix.

Hate crime laws was effective in the first two years. However, the effect somehow decayed. In 1995 - 1997, not only the treatment group showed a increasing hate crime trend. **Figure 3** shows that Maryland (adopted hate crime laws in 1990) and South Dakota (adopted hate crime laws in 1993) also showed significant increases in 1995 - 1997. However, in 1994 - 1995, the treatment group states were the only states that showed a decreasing hate crime statistics.

Hate crimes are often driven by political event, immigration status, social movements, etc. A possible explanation is that in 1995 - 1997 there were such incidents that drove the hate crimes in some particular states.

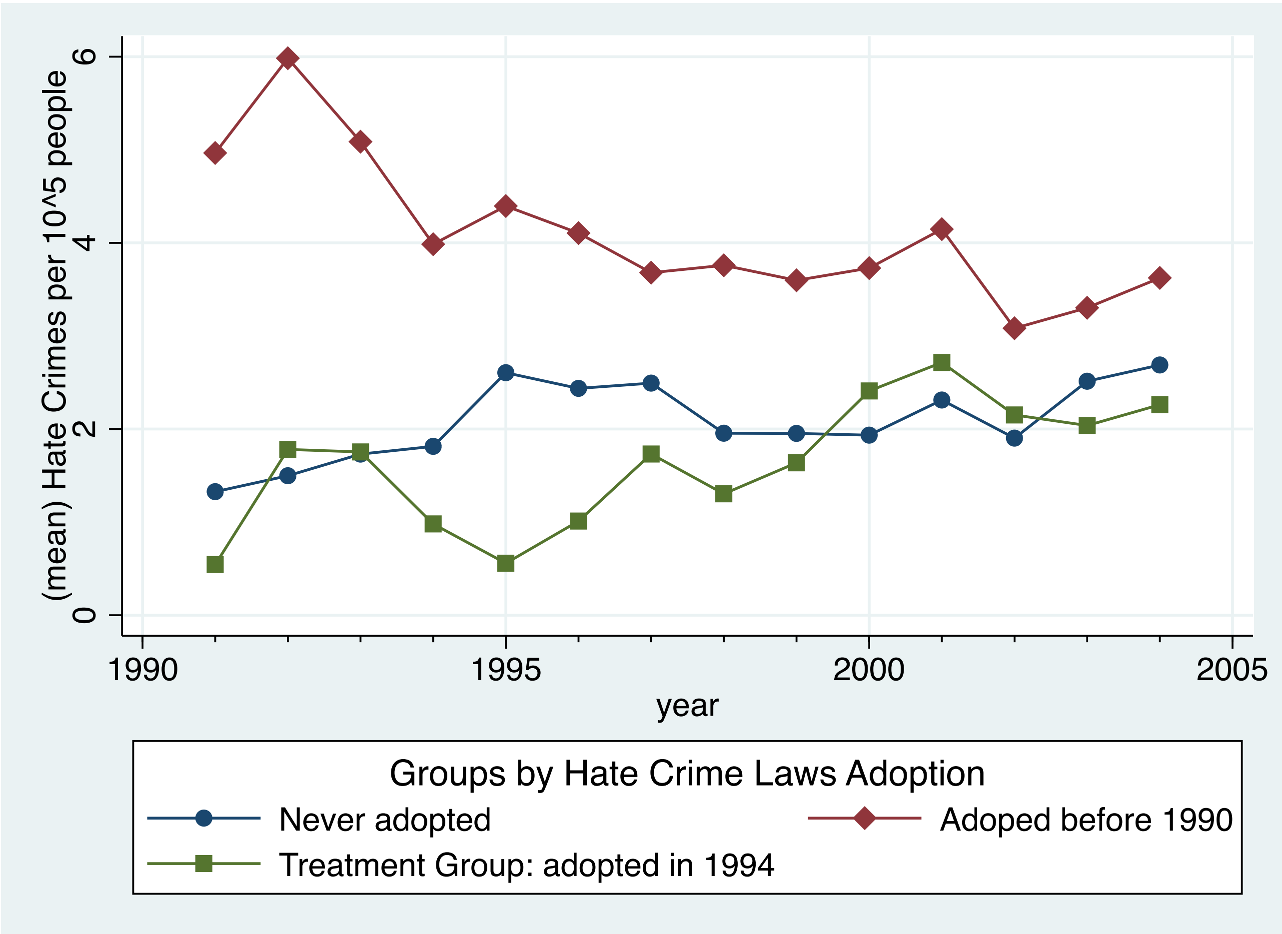

FIGURE 2: Green line (1994) is the average hate crime rate for the treatment group. The blue line (0) corresponds to states that never adopted hate crime laws. The red line (1990) corresponds to the states that adopted hate crime laws before 1990. The hate crime rate are normalized to hate crime rate per 10^5people.

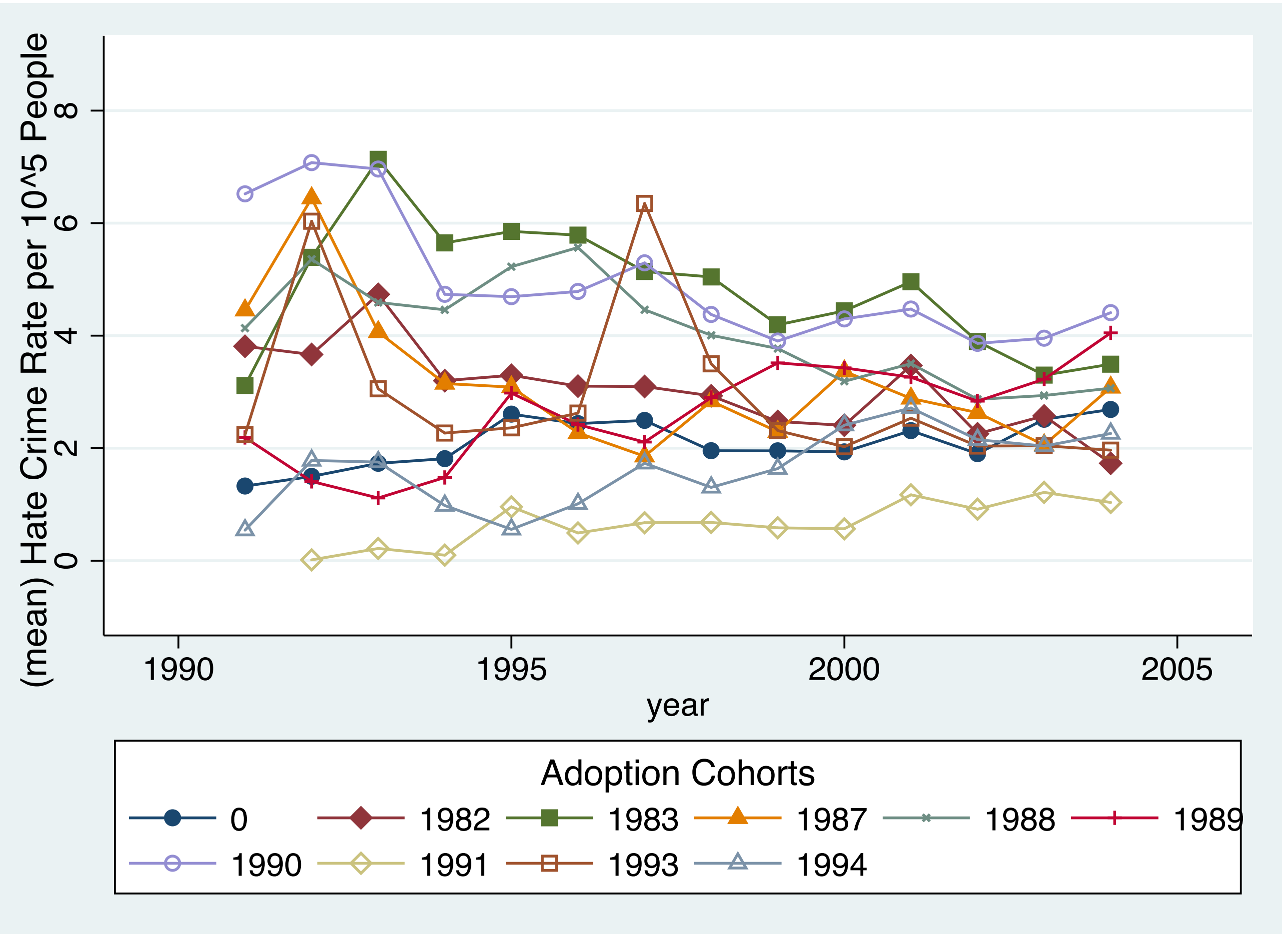

Figure 3: Hate Crime Statistics by Adoption Cohorts.

Among the aforementioned three aspects of a state (basic education, political ideology and economics), only political ideology (*conservative*) showed a statistically significant result. However, it is counter-intuitive that more conservative states had less hate crimes, as the literature showed that being liberal would lead to less hate crimes (Jacobs and Henry, 1995).

5.1 Validity & Robustness

First, it is trivial that for the residents, the treatment shock is random — the individual could not control the timing and the state where the adoption of hate crime laws happened. Second, the adoptions are hard predictable by state features due to the complexity of the legislation system (Soule and EarL, 2001). Therefore, the treatment could be regraded as random for individuals.

To test the robustness of our result, I employed "Placebo Test". I ran the regression (**Equation 3**), however, I assigned the cohort of 1990 as the pseudo-treatment group, while keeping the year of interest 1994 untouched. The result showed a very insignificant result for the treatment effect, as shown in **Table 7** (in Appendix).

6 Discussion & Conclusion

In this research, my regression result can confirm a statistically significant treatment effect using Difference-in-Difference analysis. The hate crime laws adoptions in Mississippi and Virginia in 1994 did showed a short-term effect that decreased the hate crimes within the two states. In addition, state's political ideology (conservative identifier) also contributed to inter-state hate crime difference.

The limitation of this research is that the data could not explain the rebound of hate crimes in 1995 - 1997. A further sociology study and more detailed data may be needed to explain the rebound.

Another limitation is that the hate crime statistics were only available after 1992. More than 30% of the states adopted the hate crime laws before 1992, however, due to the statistics availability issue, I could only analyze the states that adopted the hate crime laws in 1900s. The scarcity of hate crime statistics is understandable. According to FBI UCR (FBI, 2012), not until 1994 did California started to comprehensively collect hate crime incidents.

If more historical hate crime statistics could be recovered using historical documents, reports, newspaper archives, we might be able to extend the research to examine and compare the hate crime law adoption effect in different periods, in different states and in different groups of states grouped by their political ideologies.

7 Appendix

Adoption Year	State
1994	Mississippi
1994	Virginia
1993	South Dakota
1993	Texas
1991	North Carolina
1990	Connecticut
1990	Iowa
1990	Maryland
1990	New Hampshire
1990	New Jersey
1989	Florida
1989	Minnesota
1989	Montana
1989	Nevada
1989	Tennessee
1989	Vermont
1988	Colorado
1988	Michigan
1988	Missouri
1987	Ohio
1987	Oklahoma
1987	Wisconsin
1987	West Virginia
1983	Idaho
1983	Illinois
1983	Massachusetts
1982	Alaska
1982	New York
1982	Pennsylvania
1982	Rhode Island
1981	Oregon
1981	Washington
1978	California

Table 4: 33 States by Hate Crime Laws Adoption Years, available from 1990 - 2016

Variables	Coefficient
treat	0.909
	(0.874)
post	-2.487***
	(0.600)
post_treat	-1.288**
	(0.558)
conservative	-0.269***
	(0.0495)
1992.year	-1.682***
	(0.397)
1993.year	-0.870**
	(0.311)
1994.year	-1.545***
	(0.467)
1995.year	1.966***
	(0.625)
1996.year	0.873
	(0.552)
1997.year	1.451**
	(0.648)
1998o.year	-
pc_inc_ann	2.65E-06
	(0.000102)
edattendrate	-0.0896
	(0.0999)
Constant	20.40*
	(10.68)
Observations	124
R-squared	0.477
Year 1998 Dummy omitted	*** p<0.01, ** p<0.05, * p<0.1

TABLE 5: Regression of **Equation 3**, extended post-treatment period to 1998. Clustered by State.

Variables	Coefficients
treat	0.704
	(0.772)
post	-1.356
	(0.841)
post_treat	-0.902
	(0.747)
conservative	-0.240***
	(0.0526)
1992.year	-1.476***
	(0.319)
1993.year	-0.741**
	(0.260)
1994.year	-1.364***
	(0.412)
1995.year	0.921
	(0.754)
1996.year	-0.0948
	(0.620)
1997.year	0.404
	(0.617)
1998.year	-0.990
	(0.574)
1999.year	0.0196
	(0.261)
2000o.year	-
pc_inc_ann	3.14E-05
	(0.000110)
edattendrate	-0.0733
	(0.0882)
Constant	17.19*
	(9.497)
Observations	160
R-squared	0.431
	*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression of **Equation 3**, post-treatment period extended to 2000. Clustered by State.

Variables	Coefficients
treat	2.659
	(1.922)
post	-3.828***
	(1.137)
post_treat	-1.505
	(1.079)
conservative	-0.252***
	(0.0748)
1992.year	-2.176**
	(0.866)
1993.year	-2.115**
	(0.819)
1994.year	-3.220***
	(0.925)
1995.year	1.397***
	(0.358)
1996o.year	-
pc_inc_ann	4.15E-05
	(0.000163)
edattendrate	-0.242
	(0.194)
Constant	35.62
	(21.79)
Observations	245
R-squared	0.175
Clustered at State level	*** p<0.01, ** p<0.05, * p<0.1

Table 7: Placebo Test Regression Result. The treatment is insignificant as expected.

8 Bibliography

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