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# The Effects of Public Policy on Charitable Giving

by

Arielle Sauer

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of the requirements for the degree of  
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## **Abstract**

This study analyzes the effects of public policy on charitable giving. More specifically, it looks at the effects of No Child Left Behind, The Affordable Care Act, and the Clean Power Plan has on charitable organizations geared towards education, healthcare and environmentalism respectively. Using IRS Business Master File data with a difference-in-differences fixed effects model, I find that public policy has a negative impact on giving to education and environmental nonprofits and a positive effect on giving to health nonprofits. Furthermore, these results show a lasting effect with an even larger impact for subsequent years of each policy. For nonprofits focused on education and environmental issues, it appears that public policy is seen as a substitute for charitable donations, while for health nonprofits, it is a complement.

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## **Introduction**

Between 2005 and 2015, the number of nonprofits in the United States has grown by 10.4%, and the total amount donated has increased by 28.4% when adjusted for inflation. In 2015, the nonprofit sector comprised 5.4% of the United States GDP (McKeever, 2018). In recent years, economists have turned their attention towards studying charitable economics and the different economic and noneconomic factors that impact it. Most of these studies, however, focus on the effects of tax policy on charitable giving (Brooks, 2007), what effects the market for giving (List, 2011), or who gives and how much (James & Sharpe, 2007). Studies on tax policy show that tax credits do lead to an overall increase in charitable giving (De Vita & Twombly, 2004). However, when looking at the effects of a nonprofit receiving direct government funding, studies indicate there is a crowding out effect for private contributions (Andreoni & Payne, 2003).

It is also possible that other non-tax related policies can impact charitable giving. Government intervention in a specific social issue by means of public policy may influence a donor's decision-making process when deciding whether to donate to a charity with the same mission. Some donors might feel that the governments increased involvement is enough to remedy the issue, and therefore, it is no longer necessary for them to donate to such a nonprofit. Alternatively, an increase in awareness caused by the new policy may galvanize individuals to donate. Though nonprofits advocate for government policies that help them achieve their mission, there has been no analysis on how implementing such policies can affect their revenue.

This study analyzes the effects of public policy on charitable giving. More specifically, it looks at the effects of No Child Left Behind, The Affordable Care Act, and the Clean Power Plan on the total revenue of charitable organizations with missions geared towards education, healthcare, and environmentalism respectively. Three different policy types are used in order to

see if donors who support a specific mission react differently than others. Evidence of this is demonstrated in Brooks' (2007) analysis of tax price elasticity for each nonprofit subsector. He finds that donors for each subsector respond differently to changes in tax policy. These policies were chosen specifically because each enacted major reform to the current systems in place.

This paper use IRS Exempt Organization Business Master File data provided by the National Center for Charitable Statistics. Though there is research on the effects of tax policy on charitable giving and research on the impacts of these policies within their own sector, there is little to no research on how these kinds federal policies affect charitable giving. Brooks (2007) and Bakija and Hiem (2008) both estimate the tax price elasticity for charitable giving, while List (2011) focuses on how charitable giving responds to the overall economic environment. I propose that the policies listed above will have a negative effect on the total revenue of nonprofits whose missions are of similar purpose.

## **Literature Review**

Extensive research has been done to determine what effects charitable giving. Majority of the literature on charitable giving focuses on three questions: what are the effects of tax policy on charitable giving, what economic and demographic factors effect charitable giving, and does government funding lead to a crowding out of donations? Looking within the literature for each policy, the focus is primarily on the effectiveness of the policy and its impact within the sector.

"Income Tax Policy and Charitable Giving" estimates the tax price elasticity of charitable giving across six different nonprofit subsectors (Brooks, 2007). Using a FIML tobit model with data from the Panel Study of Income Dynamics, Brooks finds that elasticity isn't constant for the six different subsects (2007). Some nonprofit giver types have a weak reaction to

tax policy changes, such as health nonprofits, while others have a stronger reaction to tax policy changes, such as combination nonprofits. Combination nonprofits are nonprofits that fit under multiple subsectors. This study showed variation in price elasticity of giving with a range of 0.58 to 2.68 for health and combination nonprofits respectively, both of which were statistically significant (Brooks, 2007). It is clear tax policy doesn't affect all subsectors equally, so treating them with a uniform elasticity can prove to be ineffective when setting tax policies.

Bakija and Hiem's (2008) estimate the elasticity of charitable giving using high-income individuals tax return data for the years 1979-96 and 1999-2005. High-income individuals were used because they account for 30 percent of overall charitable giving and they experienced the most variation in tax incentive during the study period. They used a two-stage least square regression and fixed effects model to estimate a log-log demand equation. Predictable changes in federal and state tax law was used as an instrument for future changes in price and income. (Bakija & Hiem, 2008). To distinguish between short-term and long-term price changes, Bakija and Hiem included lagged and future changes in price and income in the model. Their analysis estimates that the elasticity of giving with respect to a persistent price change is about -0.7 (Bakija & Hiem, 2008).

In "The Nature and Cause of the U-shaped Charitable Giving Profile" (2007), James and Sharpe examine why the charitable giving profile is U-shaped using data from the U.S Department of Labor's Consumer Expenditure Survey. In the U.S the lowest and highest income brackets give the highest percent of their incomes to charity, creating the U-Shape profile. This was often believed to be caused by highly devoted, lower income households donating to religious organizations (James & Sharpe, 2007). This study, however, provides more insight. James and Sharpe find that retirement age households who are considered low-income but retain

high-assets are a contributing factor to the U-Shape charitable giving profile. Of households that are committed to charitable giving, committed being defined as a household that gave 10% or more of their income, 48% of the households making \$30,000 or less were retirement age households compared to 15% who earn \$80,000.00 or more (James & Sharpe, 2007).

John List's paper "The Market for Charitable Giving" (2011) discusses the effects of the S&P 500 stock price index on charitable giving. In this paper he finds that not only is charitable giving more responsive to positive increases in the S&P 500 than decreases, but that 40% of the percentage change in variation of charitable giving is accounted for by the variation in percentage change from the S&P 500 one year before. His results show that a 1% increase in the S&P 500 correlated with a 0.19% increase in charitable giving the following year. In the same paper he found that Religious organizations are less responsive to changes in the S&P 500 and that lower income individuals are more likely to donate to these types of organizations (List, 2011).

In Hartmann and Werding (2012) paper, they explore if volunteering time and donating money are substitutes or complements. They use data from the European Social Survey from 2002-2003. The data set provides information on charitable behavior and civic engagement from charitable organizations across 22 European countries (Hartmann & Werding, 2012). Using a bivariate probit model, the study found that donating time and money were complements instead of substitutes. For individuals who only donated time, having an average and above average income had a positive effect on the probability that an individual donates. If donating time was a substitute of donating money, higher incomes would see a negative effect on donating since it would be more costly (Hartmann & Werding, 2012).



In “Motivational Crowding Out Effect in Charitable Giving: Experimental Evidence,” (2020) Muller and Rau utilize a modified dictator game to measure crowding out effects for donation motivations. Their experiment consists of four parts. The first two parts allow them to determine a subject’s guilt parameters and risk preferences before the two donation phases (Muller & Rau, 2020). In the first donation phase, subjects choose an amount to donate to the German Red Cross and are previously informed that there will be three states of donating. All donation states have the same probability of being chosen for each subject and once they choose a donation amount, their state will be revealed (Muller & Rau, 2020). The neutral state is used as a benchmark, the reimbursement state results in 50% of the amount they chose to donate being reimbursed back to them, and subjects matched to the subsequent payment state are required to pay an extra 50% of the donation amount. The second donation phase, subjects once again choose an amount to donate, but there were no price effects after donating (Muller & Rau, 2020). The experiment found that overall, donations decrease from the first donation round to the second, and there are no statistical differences between the reimbursement and subsequent price state. It also found that individuals with a high guilt parameter donate more at the first donation opportunity, but during the second donation opportunity they donate more than two times less after having experienced a price effect than those who experienced no effect (Muller & Rau, 2020). A replication study was performed using subjects who have previously participated in an economic study. The results supported the previous studies’ outcomes.

Andreoni and Payne’s paper “Do Government Grants to Private Charities Crowd Out Giving of Fund-raising?” (2003) they discuss if nonprofits reduce fundraising efforts after receiving a government grant. Using tax return data from 1982-1998 of 534 social service nonprofits and 233 art nonprofits, they confirm this hypothesis (Andreoni & Payne, 2003). A

two-stage least square regression is used to estimate the relationship between government funding and fundraising expenditures, with National Institute of Health Funding lagged by one year as an instrument. Andreoni and Payne found that art organizations see an average decrease of \$264 in fundraising expenditures for every \$1,000 of government grants they receive, and social service organizations see an average decrease of \$54 for every \$1,000 of government grants they receive (Andreoni & Payne, 2003). Both estimates are statistically significant.

Research by de Andres-Alonso et al. analyzes the effects of public grants on private charitable giving for 67 international cooperation and development nonprofits in Spain. In “The Impact of Public Funding on the Different Types of Private Contributions” (2019), they find that there is partial crowding-out effect from public grants. Using a generalized method of moments, the results show that private contributions decreases by €0.43 for every €1.00 received (de Andres-Alonso et al., 2019). When looking further into the effects of public grants on the different types of private giving, the results are slightly different. Though there is a general negative effect for all private giving types, de Andres-Alonso et al. find that have the largest negative effect is on individual one-time donations. One-time donations see a decrease of €0.17 for every €1.00 of public grants received, while periodic donations see a decrease of €0.08 for every €1.00 of public grants received (de Andres-Alonso et al., 2019). Both these results are statistically significant. Corporate donations and revenue from sales also see a negative effect, but the results are not significant. De Andres-Alonso et al. suggest that for corporations, this may be because the nonprofits in their data receive most of their funding from public grants, so they are not investing as much of their fundraising efforts into these other revenue generating efforts (2019).

“Crowding Out and Crowding In of Private Donations and Government Grants” examines if crowding out also happens in the opposite direction (Heutel, 2014). Heutel investigates if increased private contributions leads to a decrease in public funding, and if government grants act as a signal of charity quality that then results in an increase private giving. To achieve this, he uses a tobit and fixed effect models, and instrumental variables with 990 form charity tax return data from 1998 to 2003 provided by the National Center for Charitable Statistics (Heutel, 2014). He uses both an organization- fixed effect variable and year-fixed effect variable. For instrumental variables he uses Supplementary Security Income programs state-level measures of government transfers to individuals and charity level membership dues provided on the 990 form (Heutel, 2014). His analysis starts by estimating the effect of government grants on charitable giving. Overall, his results suggest that for every \$1 increase in government grants there is a \$0.10 to \$0.30 increase in private donations. He then examines the effects of private giving on government grants. The results for this are mixed and insignificant, indicating that there is no effect (Heutel, 2014). Lastly, he examines the potential crowding in effect of government grants. Heutel find the charity quality signal from receiving a government grant is stronger for younger nonprofits. The results show that the crowding in effect decreases by 1 to 2 cents for each year the charity has been open. The results also indicate that government grants start crowding out individual donations at about 40 years of age (Heutel, 2014).

Simmons and Emanuele expand on the crowding out effects of government funding by evaluating how it impacts volunteering. In “Does Government Spending Crowd Out Donations of Time and Money?” they analyze the impact of local and state level government expenditures on donations of time and finances (Simmons & Emanuele, 2004). To do this, they utilize data from *Giving and Volunteering, 1996* that is collected by the Gallup Organization and the

Independent Sector, and *Government Finances* provided by the Department of Finance.

Simmons and Emanuele find that donations of finances and time both decrease when there is an increase in local and state government expenditures (Simmons & Emanuele, 2004). Though the impacts of government expenditures are negative, the coefficients are significantly small in both cases, and therefore are not likely to have much of an economic impact.

On January 8th, 2002, President George W. Bush signed the No Child Left Behind Act into law. This act required states to test and report on students in grades 3 through 8, and again in high school. The purpose of this act was to bring all students up to a proficient level of math and reading by the 2013-14 school year (Klein, 2015). Each state defined their own proficiency levels and how to test for it. Schools who failed to meet the minimum yearly standard were required to allow students to transfer to better performing schools and to provide free tutoring for students. Under extreme cases, the state would intervene (Klein, 2015). By 2010, it was clear that most states were not going to meet their proficiency levels and the act was replaced by the Every Student Succeeds Act.

In Wang and Fahey's (2011) study, they analyze the effect of No Child Left Behind on parental volunteering in schools. They use a logistic regression and a generalized linear model on cross-sectional data from the Current Population Survey. The study found that there is a decrease in the rate in which parents volunteer from 2002 to 2008 (Wang & Fahey, 2011). The results also show that those who live in metropolitan areas were less likely to volunteer than their counterparts. When accounting for differences in demographics, they find that white women who are citizens are the most likely to volunteer. Another finding is that "Hispanic parents in the West are more likely to volunteer for education than their counterparts in the Northeast and South region" (Wang & Fahey, 2011). All these results are found to be statistically significant.

As stated earlier, Hartmann and Werding (2012) found that volunteering time is a compliment to donating money. From this, it is easy to see the possible links between public policy and charitable giving.

The Affordable Care Act was signed into effect on March 23, 2010, with further amendments signed in on March 31st, 2010. The act aimed to expand access to healthcare, further protect consumers, and improve the overall healthcare system (“The Affordable Care Act,” 2011). It planned to achieve this goal by creating a timeline in which specific provisions were to be set in place. The most notable being the expansion of Medicaid to low income individuals, requiring individuals to have healthcare coverage and for employers to cover their workers, and prohibiting insurance companies from denying coverage for preexisting conditions. Failure to meet the deadline resulted in a penalty for individuals and companies (“The Affordable Care Act,” 2011).

The Clean Power Plan was announced on August 3, 2015. The policy’s objective was to cut carbon emissions produced by power plants to 32% below was produced in 2005 (FACT SHEET: Overview of the Clean Power Plan, 2017). To achieve this, the EPA sets interim and final goals for each state. The goal is set in three different forms as to provide flexibility on how each state chooses to meet it. State then produce their own plan for their power plants on how to achieve lower CO2 levels. The plans are required to be submitted by September 6, 2016 and each plan must include arrangements that show it is making progress. Interim goals are to be achieved during the 2022 -2029 period and final CO2 goals are to be achieved by 2030 (FACT SHEET: Overview of the Clean Power Plan, 2017).

While there is extensive research on the effects of tax policy and government funding on charitable giving, there is none that analyze the effects that government policies have on the

revenue of nonprofits who aim to achieve the same mission. Furthermore, the literature supports that government funding leads to a crowding out of private donations. It is entirely possible that other forms of government intervention are producing a similar crowding out effect.

## **Data**

The IRS Business Master File (BMF) data provided by Urban Institute National Center for Charitable Statistics and the National Bureau of Economic Research is used for this analysis. The IRS Business Master File is a comprehensive list of exempt organizations that is updated and published on a monthly basis. The BMF contains limited information about each organization that was provided on their most recent 990 Form, such as the organizations EIN number, the end date of the most recent tax period filed, and total revenue claimed. The Urban Institute pulls the data from the IRS database at random times throughout the year. Any information that may have been updated in the time between data pulls is included in the latest version. For the analysis on education and health, the BMF data provided from Urban Institute is utilized. When dealing with the Environmental analysis, the 2017 tax period data provided by the Urban Institute contained incomplete information. However, The National Bureau of Economic Research provides such data. NBER only provides BMF data for 2013 onward, so it could not be used for the entire study. Both sources provide the data for October 2013, so key variables are compared in the data to verify that the files are essentially the same. The small level of discrepancy could be attributed to when each organization downloaded the information in comparison to when the IRS had updated it. It could also be attributed to the Urban Institutes validation process later done with the NCCS core files.

For income and poverty variables, data available through the US Census Bureau is utilized. The Census Bureau provides Small Area Income and Poverty Estimates which contains the median household income and percent of individuals in poverty on a county level. These were matched using the FIPS code provided in the NCCS Core files.

Lastly, Yahoo Finance provides information on the S&P 500. Yahoo Finance provides the daily open, close, high, and low prices for each day. They also provide the daily volume of the stock. For this analysis, the S&P 500 variable is measured as the average closing amounts for ten-to-fourteen months prior to the nonprofits 990 tax filing date. This range allows for any ongoing trends that influence an individual's donation decision to be captured.

## **Methodology**

To evaluate the effects of public policy on charitable giving, this study uses a three-period difference-in-differences fixed effect model. For this analysis, let  $t = 0,1,2$  where  $t$  is the indicator for period. The period before the policy is denoted as  $t = 0$ , the first year after the policy is denoted as  $t = 1$ , and subsequent years of policy are denoted as  $t = 2$ . Let  $Z = 1$  be treated and zero otherwise. Treatment is defined as a nonprofit whose National Taxonomy of Exempt Entities (NTEE) classification code matches that of the policy being analyzed. For example, nonprofits with NTEE code ED (education) are used as the treatment group for the No Child Left Behind analysis.  $I_t$  is the indicator for the period where  $I_t$  is 1 for period  $t = 0,1,2$  and zero otherwise.  $X_{it}$  are the other covariates controlled for in the analysis, such as median household income, percent of individuals in poverty, and the average S&P 500 one year prior. The estimated equation takes the form

$$(1) \text{ Total Revenue}_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 I_{it=2} + \beta_3 I_{it=3} + \beta_4 I_{it=2} * Z_{it=2} + \beta_5 I_{it=3} * Z_{it=3} + \beta_{it} X_{it} + \epsilon_i$$

with the difference- in-differences for the first year as

$$(2) DID_1 = (E[Z = 1, t = 2] - E[Z = 1, t = 1]) - (E[Z = 0, t = 2] - E[Z = 0, t = 1]) = \beta_4$$

and the difference- in-differences for the second year as

$$(3) DID_2 = (E[Z = 1, t = 3] - E[Z = 1, t = 1]) - (E[Z = 0, t = 3] - E[Z = 0, t = 1]) = \beta_5$$

Combined with a fixed- effects model, the equation takes the form

$$(4) \text{ Total Revenue}_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 I_{it=2} + \beta_3 I_{it=3} + \beta_4 I_{it=2} * Z_{it=2} + \beta_5 I_{it=3} * Z_{it=3} + \beta_{it} X_{it} + \delta_c + \epsilon_i$$

where  $\delta_c$  is the nonprofit level fixed effect. The model above is also analyzed while filtering out nonprofits whose revenue is positive, and then further filters out the bottom 10<sup>th</sup> percentile of revenue. This is done to reduce any potential bias caused by nonprofits who are consistently in bad financial health and run yearly deficits. Furthermore, a weighted fixed effects model is used to reduce the effect of extremely small nonprofits on the model output.

The weight is calculated such that

$$(5) W_i =$$

$$\sqrt{(Average Revenue_i - Minimum Revenue) / (Maximum Revenue - Minimum Revenue)}$$

Combined with the previous model, the equation becomes

$$(6) \text{ Weighted Total Revenue}_{it} = \beta_0 + \beta_1 Z_{it} + \beta_2 I_{it=2} + \beta_3 I_{it=3} + \beta_4 I_{it=2} * Z_{it=2} + \beta_5 I_{it=3} * Z_{it=3} + \beta_{it} X_{it} + \delta_c + \epsilon_i$$



## Results

Table 4 below shows the effects of No Child Left Behind on charitable giving. The first model is a difference-in-differences fixed effects model, the second is a fixed effects model that removes the bottom ten percent of nonprofits whose total revenue is positive, and the third model is a weighted fixed effects model. All three models yield negative results on revenue for education focused nonprofits after the policy is signed into effect. The first basic model indicates that education nonprofits receive an average of \$669,202 less revenue the first year after the policy and an average of \$761,104 less revenue for the subsequent years of the policy. Both results are statistically significant at the 0.1% level. As expected, the second model shows a similar effect, with education nonprofits receiving \$836,276 less the first year after the policy and \$911,782 less the subsequent years of the policy. Again, these results are significant at the 0.1% level. This slight increase can be attributed to the dropping of charities whose income is in the lowest 10%. Doing so has removed nonprofits who were already in poor financial standing, such as bankruptcy, or so particularly small that they would see very little variation in their revenue. The third model shows the greatest negative effect, with education nonprofits receiving \$3,070,087 less the first year after the policy and \$3,292,315 less the subsequent year. Both these results are statistically significant at the 1% level. As one would suspect, these results indicate that larger education nonprofits suffer a proportionally greater loss of revenue after No Child Left Behind is initiated. Such results indicate that public policy geared towards education is a substitute for donations to education nonprofits. They also indicate a lasting effect past the first year of the policy, since all the models show an even larger decrease in donations for subsequent

years of the policy. Donors to these charities likely believe that the government's intervention is enough for them to lower or stop their donations and redistribute those funds elsewhere.

Table 5 shows the effects of the Affordable Care Act on charitable giving. Like table 4, the first model is a difference-in-differences fixed effects model, the second is a fixed effects model that removes the bottom ten percent of nonprofits whose total revenue is above zero, and the third model is a weighted fixed effects model. Overall, the models indicate that public policy has a positive effect on the revenue of health nonprofits. The first model indicates that health nonprofits saw an average increase of \$560,745 the first year after the policy and an average increase of \$844,388.55 in the subsequent years of the policy. These results are statistically significant at the 0.1% level. The second model shows a slightly larger effect, indicating that health nonprofits receive an average of \$704,752 more the first year after the policy and \$1,049,034 the subsequent years of the policy. These results are also statistically significant at the 0.1% level. Like before, this increase can be attributed to dropping nonprofits in the bottom 10% of revenue, and therefore likely to see very little variation in revenue. The final model shows a larger effect, with health nonprofits seeing an average increase of \$2,287,859 in revenue the first year after the policy and an average increase of \$3,713,182 the subsequent years. The first-year results are statistically significant at the 0.1% level and the subsequent year results are statistically significant at the 5% level. The change in effect from education nonprofits to health nonprofits can potentially be attributed to the wider range of purpose within the health nonprofit subsector. Nonprofits categorized under health can range from hospitals to nonprofits focused on finding a cure for specific illnesses. While the Affordable Care Act aims to provide better, affordable healthcare to everyone, it is easy to see how some health nonprofits, such as American Cancer, wouldn't see a decrease in revenue after such a policy takes effect.

Table 6 shows the effects of the Clean Power Plan on charitable giving using the same three models. Like the education analysis, all three models show a negative effect on revenue for environmental nonprofits after the policy is signed into effect. The first model shows that environmental nonprofits receive an average of \$116,985 less revenue the first year after the policy and \$339,805 less after the subsequent years. The first-year results are statistically significant at the 5% level and the subsequent year results are significant at the 0.1% level. The second model produced similar results, with an average decrease of \$137,387 in revenue for the first year and an average decrease of \$404,777 for the subsequent years. The first-year results are significant at the 5.2% level and the subsequent year results are significant at the 0.1% level. Like the education and health analysis, the third model indicates a larger effect. For the first year of the policy, environmental nonprofits receive an average of \$943,422 less of revenue, and for the subsequent year they receive an average of \$2,580,922 less revenue. The first-year results are significant at the 10% level, while the subsequent year is significant at the 1% level. Like the education results above, these results show that larger environmental nonprofits suffer a greater decline in revenue after the Clean Power Plan is signed, and that the decline continues past the first year with an even larger decline in the subsequent years. These results indicate that public policy focused on environmentalism is a substitute for donations to environmental nonprofits.

## **Conclusion**

The nonprofit sector is steadily increasing in size and in percent of GDP for the United States. With this growth, it is important to look at the different economic factors that can affect this industry from year-to-year. This study has found that for education and environmental nonprofits, that public policy acts a substitute for charitable giving, but for health nonprofits it

acts as a compliment. The negative effects found for the education and environmental nonprofits also implies that there is some confidence in the U.S government's ability to properly implement these policies. Though public policy seems to act as a compliment for health nonprofits, it will take further analysis into the effects on the different subsectors to be certain.

## Tables

Table 1: No Child Left Behind Analysis Summary Statistics

Variables	Observations	Mean	Standard Deviation
Total Revenue	469,710	\$4,370,922	\$62,670,543
First Year of Policy	469,710	0.33	0.47
Subsequent Years of Policy	469,710	0.33	0.47
Treated	469,710	0.15	0.36
First Year of Policy*Treated	469,710	0.05	0.22
Subsequent Years of Policy*Treated	469,710	0.05	0.22
Median Household Income	469,710	\$44,572	\$10,869
Percent in Poverty	469,710	11	4
Average S&P 500	469,710	\$1,03	\$10

Table 2: Affordable Care Act Analysis Summary Statistics

Variables	Observations	Mean	Standard Deviation
Total Revenue	793,998	\$1,818,899	\$37,802,397
First Year of Policy	793,998	0.33	0.47
Subsequent Years of Policy	793,998	0.33	0.47
Treated	793,998	0.08	0.27
First Year of Policy*Treated	793,998	0.03	0.16
Subsequent Years of Policy*Treated	793,998	0.03	0.16
Median Household Income	793,954	\$52,704	\$13,630
Percent in Poverty	793,954	14	5
Average S&P 500	793,998	\$1,097	\$158

Table 3: Clean Power Plan Analysis Summary Statistics

Variables	Observations	Mean	Standard Deviation
Total Revenue	1,048,599	\$4,013,961	\$112,455,739
First Year of Policy	1,048,599	0.33	0.47
Subsequent Years of Policy	1,048,599	0.33	0.47
Treated	1,048,599	0.05	0.21
First Year of Policy*Treated	1,048,599	0.02	0.12
Subsequent Years of Policy*Treated	1,048,599	0.02	0.12
Median Household Income	1,048,527	\$60,129	\$16,331
Percent in Poverty	1,048,527	14	4
Average S&P 500	1,048,599	\$1,946	\$115

Figure 1: Total Monthly Revenue for No Child Left Behind Analysis

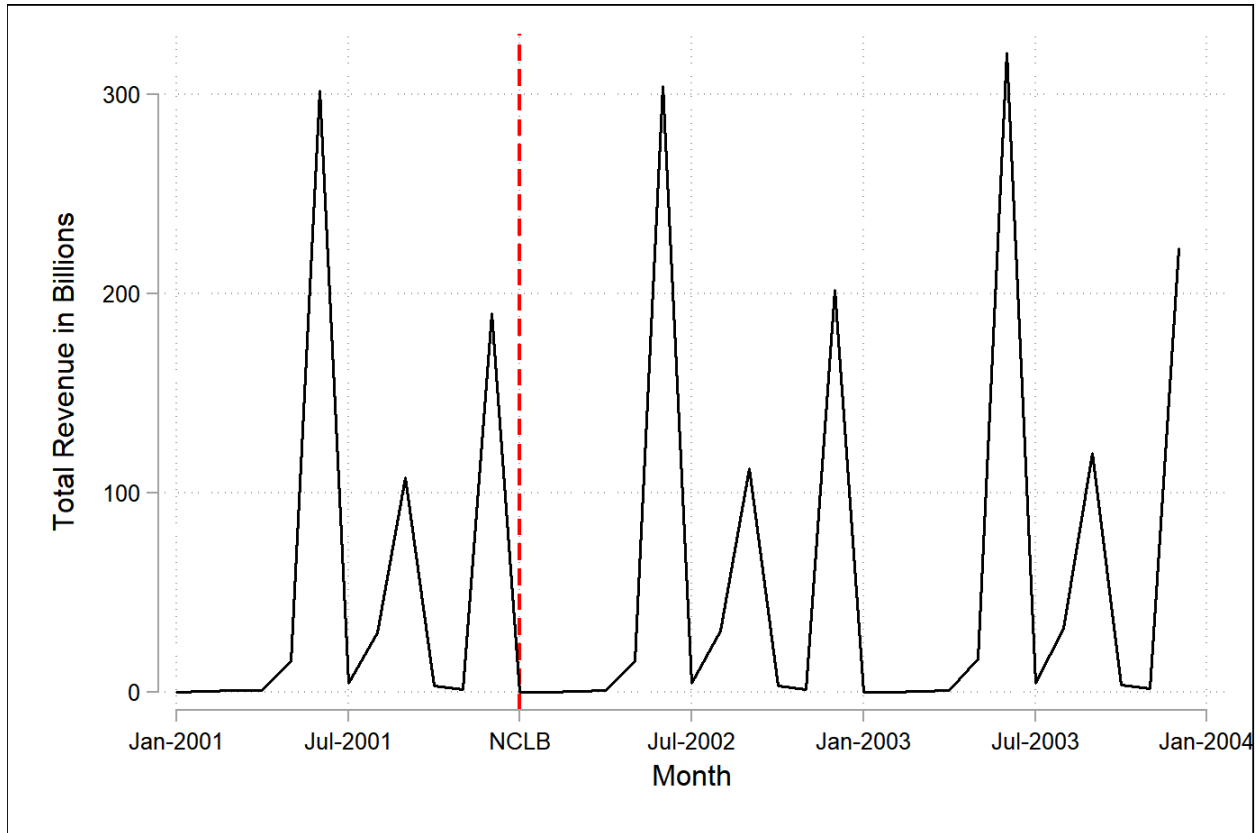




Figure 2: Total Monthly Revenue for Affordable Care Act Analysis

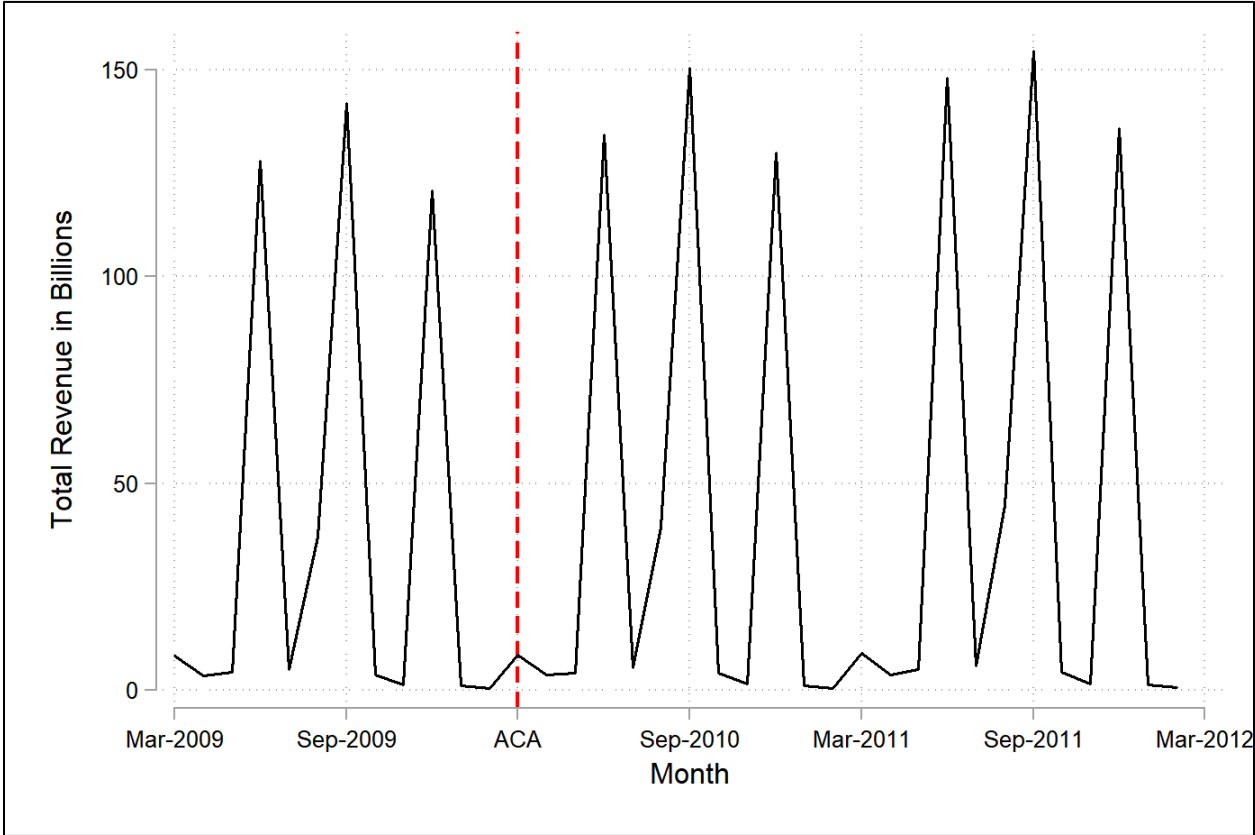


Figure 3: Total Monthly Revenue for Clean Power Plan Analysis

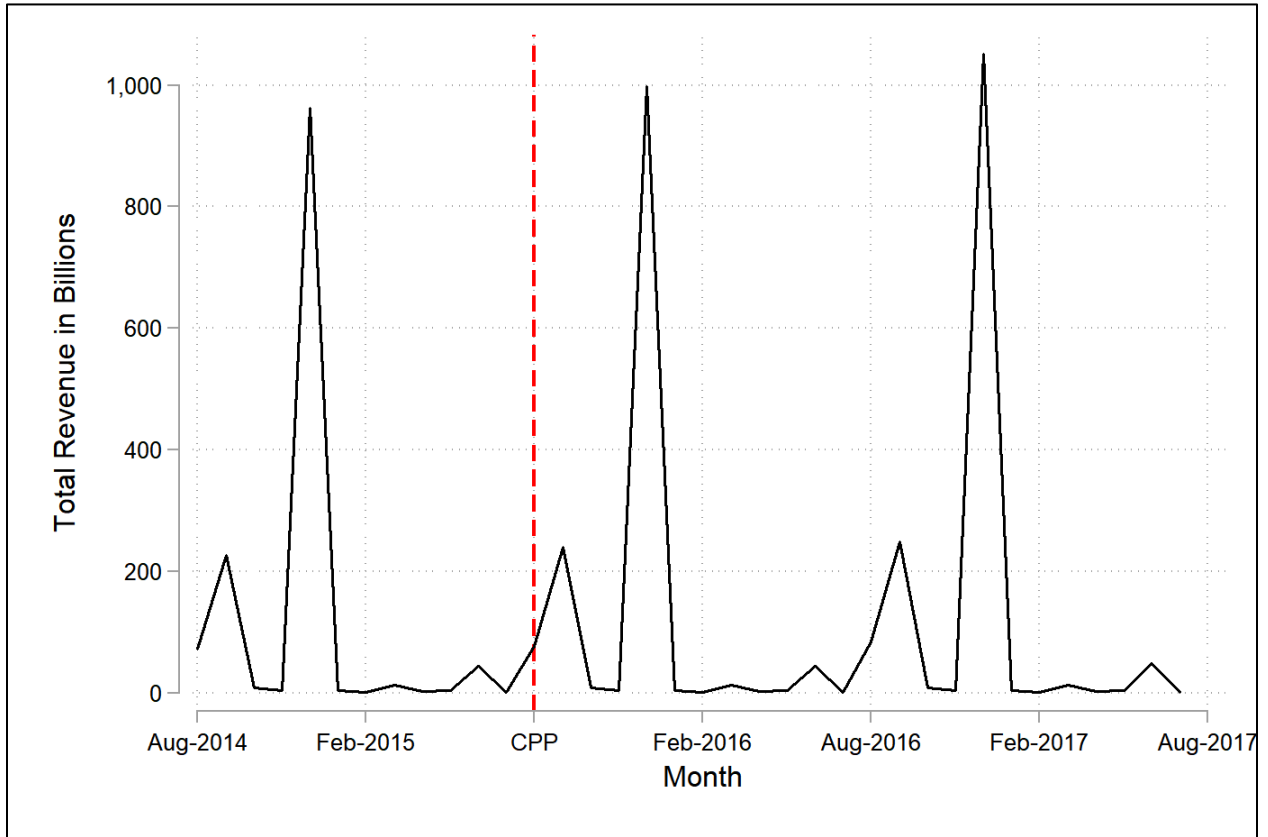


Table 4: No Child Left Behind Estimates

	Fixed Effects	Fixed Effects > 40,000	Weighted Fixed Effects
First Year of Policy*Treated	-669,202.91*** (163,979.29)	-836,276.02*** (211,725.42)	-3,070,087.66** (1,157,778.03)
Subsequent Years of Policy*Treated	-761,104.67*** (149,210.64)	-911,782.58*** (190,194.07)	-3,292,315.22** (1,027,048.93)
First Year of Policy	164,118.05 (90,508.44)	177,648.00 (109,088.87)	1,520,273.49 (1,233,070.41)
Subsequent Years of Policy	512,021.38*** (77,659.23)	586,036.88*** (91,144.89)	2,410,604.01 (1,256,932.08)
Average S&P 500	-247.97 (372.68)	-349.97 (451.43)	2,462.69 (4,336.89)
Constant	4,474,501.37*** (430,146.14)	5,349,216.35*** (520,491.25)	9,511,967.70 (5,254,820.10)
Observations	469,710	397,698	469,707

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 5: Affordable Care Act Estimates

	Fixed Effects	Fixed Effects > 20,000	Weighted Fixed Effects
First Year of Policy*Treated	560,746.39*** (127,842.95)	704,752.35*** (168,571.26)	2,287,859.37*** (618,363.35)
Subsequent Years of Policy*Treated	844,388.55*** (231,697.10)	1,049,034.67*** (305,186.96)	3,713,182.48* (1,552,012.27)
First Year of Policy	51,637.73** (17,161.77)	78,896.95** (27,807.67)	57,658.68 (98,288.24)
Subsequent Years of Policy	159,377.25*** (25,850.65)	270,696.65*** (46,107.95)	551,027.93** (174,826.29)
Average S&P 500	-80.42 (61.21)	-243.76* (112.13)	-723.93 (400.53)
Constant	1,800,464.54*** (58,372.73)	2,966,634.63*** (103,786.54)	5,986,659.62*** (373,734.25)
Observations	793,998	503,073	793,995

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 6: Clean Power Plan Estimates

	Fixed Effects	Fixed Effects > 25,000	Weighted Fixed Effects
First Year of Policy*Treated	-116,985.79* (58,930.85)	-137,387.76 (70,569.28)	-943,422.63 (548,433.84)
Subsequent Years of Policy*Treated	-339,805.90*** (67,949.27)	-404,777.62*** (81,292.43)	-2,580,922.66** (905,996.36)
First Year of Policy	-488,810.22** (167,430.54)	-496,652.07** (189,618.95)	-1,802,038.42 (1,775,579.20)
Subsequent Years of Policy	-230,734.14 (159,158.61)	-196,324.44 (182,192.14)	-106,315.79 (1,924,306.87)
Average S&P 500	2,800.21*** (703.43)	2,965.21*** (791.12)	12,275.15 (6,539.56)
Constant	-1,190,497.76 (1,264,707.66)	-757,827.42 (1,421,453.82)	-893,574.48 (11,598,478.18)
Observations	1,048,599	881,211	1,048,596

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## References

- Andreoni, James, and A. Abigail Payne. (2003). Do Government Grants to Private Charities Crowd Out Giving or Fund-raising?. *American Economic Review*, 93 (3): 792-812.
- Bakija, Jon, Heim, Bradley. (2008). How Does Charitable Giving Respond to Incentives and Income? Dynamic Panel Estimates Accounting for Predictable Changes in Taxation. *National Bureau of Economic Research*. Retrieved June 13, 2019, from <https://www.nber.org/papers/w14237>
- Brooks, Arthur C. (2007). Income Tax Policy and Charitable Giving. *Journal of Policy Analysis and Management*, John Wiley & Sons, Ltd., vol. 26, pages 599-612, Spring.
- Clotfelter, Charles T. (1990). The Impact of Tax Reform on Charitable Giving: A 1989 Perspective. *National Bureau of Economic Research*. Retrieved June 02, 2019, from <https://www.nber.org/papers/w3273>
- de Andres-Alonso, P, Garcia-Rodriguez, I, Romero-Merino, ME (2019). The Impact of Public Funding on the Different Types of Private Contributions. *Financial Accountability & Management*. 36: 33– 49. <https://doi-org.proxy.wexler.hunter.cuny.edu/10.1111/faam.12215>
- De Vita, Carol J., Twombly, Eric C. (2004). Charitable Tax Credits Boons or Bust for Nonprofits?. *Charting Civil Society* Retrieved June 02, 2019, from <http://webarchive.urban.org/publications/311036.html>
- Exempt Organizations Business Master File Extract (EO BMF). (2019, March 12). Retrieved from <https://www.irs.gov/charities-non-profits/exempt-organizations-business-master-file-extract-eo-bmf>
- FACT SHEET: Overview of the Clean Power Plan | Clean Power Plan | US EPA.* (2019). *19january2017snapshot.epa.gov*. Retrieved March 28, 2019, from <https://19january2017snapshot.epa.gov/cleanpowerplan/fact-sheet-overview-clean-power-plan .html>
- Hartmann, Bastian, Werding, Martni. (2012). Donating Time or Money: Are They Substitutes or Complements? *Pappers.ssrn.com*. Retrieved November 12, 2019, from [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2084100](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2084100)
- Heutel, G. (2014). Crowding Out and Crowding In of Private Donations and Government Grants. *Public Finance Review*, 42(2), 143–175. <https://doi.org/10.1177/1091142112447525>
- IRS Form 990 Data - SOI Tax Stats - Exempt Organization Business Master File Data. (2019). *Nber.org*. Retrieved March 28, 2019, from <https://www.nber.org/data/soi-tax-stats-exempt-organizations-business-master-file-form-990.html>

- James, R. N., & Sharpe, D. L. (2007). The Nature and Causes of the U-Shaped Charitable Giving Profile. *Nonprofit and Voluntary Sector Quarterly*, 36(2), 218–238. <https://doi.org/10.1177/0899764006295993>
- Klein, A. (2015, April 10). *No Child Left Behind Overview: Definitions, Requirements, Criticisms, and More*. *Education Week*. Retrieved March 28, 2019, from <https://www.edweek.org/ew/section/multimedia/no-child-left-behind-overview-definition-summary.html>
- List, John A. (2011). The Market for Charitable Giving. *Journal of Economic Perspectives*, 25(2), 157-80.
- McKeever, Brice S. (November 2018). The Nonprofit Sector in Brief 2018: Public Charities, Giving, and Volunteering. Retrieved from <https://nccs.urban.org/publication/nonprofit-sector-brief-2018#the-nonprofit-sector-in-brief-2018-public-charities-giving-and-volunteering>
- Muller, Stephan & Rau, Holger A. (2020). Motivational Crowding Out Effects in Charitable Giving: Experimental Evidence. *Journal of Economic Psychology*, 76. <https://doi.org/10.1016/j.joep.2019.102210>
- National Bureau of Economic Research. (2017). IRS Form 990 Data - SOI Tax Stats - Exempt Organization Business Master File Data. [Data files and Data dictionary]. Available <https://www.nber.org/data/soi-tax-stats-exempt-organizations-business-master-file-form-990.html>
- Simmons, Walter O., Emanuele, Rosemarie (2004). Does Government Spending Crowd Out Donations of Time and Money?. *Public Finance Review*, 32(5), 498-511.
- Small Area Income & Poverty Estimates Program, C. (2019). *Small Area Income and Poverty Estimates - Interactive Data and Mapping - U.S. Census Bureau*. *Census.gov*. Retrieved 28 March 2019, [https://www.census.gov/data-tools/demo/saipe/saipe.html?s\\_appName=saipe&map\\_yearSelector=2010&map\\_geoSelector=aa\\_c&s\\_year=2010&menu=map\\_proxy](https://www.census.gov/data-tools/demo/saipe/saipe.html?s_appName=saipe&map_yearSelector=2010&map_geoSelector=aa_c&s_year=2010&menu=map_proxy)
- State and County Estimates for 2001. (2017, May 24). Retrieved from <https://www.census.gov/data/datasets/2001/demo/saipe/2001-state-and-county.html>
- State and County Estimates for 2002. (2017, May 24). Retrieved from <https://www.census.gov/data/datasets/2002/demo/saipe/2002-state-and-county.html>
- State and County Estimates for 2003. (2017, May 24). Retrieved from <https://www.census.gov/data/datasets/2003/demo/saipe/2003-state-and-county.html>
- The Affordable Care Act: A Brief Summary. (2011, March). *Ncs1.org*. Retrieved March 28, 2019, from <http://www.ncsl.org/research/health/the-affordable-care-act-brief-summary.aspx>

Urban Institute, National Center for Charitable Statistics. (2001-2003). Internal Revenue Service, Exempt Organizations Business Master File. [Data files and Data dictionary].  
<https://nccs-data.urban.org>

Urban Institute, National Center for Charitable Statistics. (2010- 2013). Internal Revenue Service, Exempt Organizations Business Master File. [Data files and Data dictionary].  
<https://nccs-data.urban.org>

Urban Institute, National Center for Charitable Statistics. (2014-2017). Internal Revenue Service, Exempt Organizations Business Master File. [Data files and Data dictionary].  
<https://nccs-data.urban.org>

Wang, Lili, Fahey, Didi (2011). Parental Volunteering: The Resulting Trend Since No Child Left Behind. *Nonprofit and Voluntary Sector Quarterly*, 40(6), 1113-1131.

*Yahoo Finance* (2019). *S&P 500 Historical Data* Retrieved April 16, 2019, from  
<https://finance.yahoo.com/quote/%5EGSPC/history?period1=978325200&period2=1071982800&interval=1d&filter=history&frequency=1d>