The Effect of the TCJA on Donations to Medical Charities

By JAMES CHANDLER

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Abstract

The Tax Cuts and Jobs Act of 2017, or TCJA, reduced the federal marginal income tax rates of most Americans. It also doubled the standard deduction, created a $10,000 cap for state and local tax (SALT) deductions, and eliminated miscellaneous itemized and casualty loss deductions. These tax policy changes resulted in the percentage of income tax filers in the US who itemize their returns to fall from approximately 30% to just 10%. Since itemization offers an incentive for charitable giving, the TCJA could be expected to drastically reduce donations for the 20% of filers who no longer itemize. Medical charities are a particularly tax sensitive and vital sector. Measuring the effect of the TCJA's reduction in giving incentive to the medical non-profit sector offers specific insights into the degree to which aggregate charitable giving was reduced. Using a dosed difference in difference model based on state-level tax cost of giving, this study estimates a -3.6 tax cost elasticity of giving to such charities accounting for a 27% smaller donation rate change in medical giving than would have occurred without the TCJA.

I. Introduction

A. Significance

The literature on the extent to which tax incentives influence charitable giving is wide-ranging and does not reach a clear consensus. This is problematic, as quantifying this effect accurately is crucial for making informed policy decisions. Any material changes to income tax rates or itemization have the potential to significantly increase or decrease an individual nonprofit's donation revenue. This diverse group of organizations, which includes charities in the social services as well as educational institutions, healthcare organizations, and religious organizations, are responsible for assisting some of America's most vulnerable populations. Special care and attention should be placed on their revenues, as even a small decline could have wide reaching impacts on struggling individuals and communities.

Previous literature has suggested that donations to medical charities are the most tax sensitive of any non-profit sector[1] and are thus a good focal point for understanding the most acute effects of the TCJA. Additionally, high quality data on medical charities are available, which makes it feasible to get accurate estimates. More importantly, this sector does critical work that is especially relevant in the current pandemic environment. Better understanding the effect of tax policy on medical giving may have implications for future public health management.

B. Tax Incentivization of Charitable Donations

First Dollar Tax Cost of Giving—

The US tax code provides filers an incentive to donate to charities by making these donations deductible expenses. Since every dollar donated is no longer considered taxable income, the "marginal price of giving" is the cost of a marginal one-dollar donation to charity when the amount saved through tax deduction is subtracted. This tax incentive to donate can be quantified by first dollar tax cost of giving, or FDTC. FDTC is simply the price of giving for a hypothetical one-dollar donation, which is often less than one dollar because of the tax incentives for those who itemize. FDTC concisely measures the degree to which tax law incentivizes an individual to donate to charity.

For itemizers, FDTC is one dollar minus their combined state and federal marginal income tax rates in decimal form. For example, an itemizing donor who has a combined marginal income tax rate of 30% spends $0.70 every time they donate one dollar to charity. For non-itemizers, the FDTC is simply one dollar, as there is no tax incentive to donate.

Last Dollar Tax Cost of Giving—

A theoretically sounder measurement of tax incentive to donate is last dollar cost of giving, or the price of donating one additional dollar to charity. In practice, this is the variable donors are most directly influenced by when choosing the size of a donation, as it considers the full tax effect for that donation. However, the last dollar cost of giving is an endogenous variable directly correlated with several other factors, such as a person's propensity to donate. It is therefore difficult to estimate without bias.

[1] Duquette (2016)

To avoid this, many studies in the literature use FDTC as an instrumental variable for last dollar cost of giving. Both variables are highly correlated and using FDTC in this manner eliminates much of the aforementioned bias. In this study, however, this strategy is infeasible, as last dollar cost of giving is not observed. As further examined later, this obstacle does not change the validity or unbiased nature of the results.

C. Previous Estimates of Tax Cost Elasticity of Charitable Giving

Over the past five decades researchers have performed an expansive number of studies seeking to calculate the elasticity of charitable giving. A meta-analysis of such studies performed by Peloza et. al found compiled estimates of elasticity across all charitable sectors combined ranging from -7.07[2] to +0.12[3] with an overall weighted mean of -1.44.[4] This mean elasticity estimate can be interpreted as: for every 1% increase in the tax price of giving to charity, the amount donated decreases by 1.44% on average. The over 100 studies included in this meta-analysis utilized a diverse range of methodologies, many with intrinsic weaknesses. Below are summaries of these methods, examinations of their shortcomings, and possible explanations beyond their broader focus as to why they estimated low, treasury inefficient, elasticities.

Methods Using Individual Tax Return Data—

The most direct data on the donation patterns of individual donors are the reported donations available through tax returns. These data, while available through the IRS in redacted form, are a poor method for analyzing the tax effect on giving for two reasons.

The largest problem with individual tax return data is selection bias, as only itemizers are incentivized to report their giving. If a tax filer is a non-itemizer, then they receive no benefit from recording and reporting their donations, and thus this information is not recorded in available data sets. This leaves only data on those, mostly wealthy, individuals who do itemize. The behavior of itemizers is likely to be substantially different from non-itemizers due to correlated characteristics, such as wealth, location, employment, or types of charities donated to. To study how a tax reform affected just these donors would likely yield narrow results with highly limited implications for large sectors of charities. Exacerbating this

[2] Robinson (1990)
[3] Wu and Ricketts (1999)
[4] Peloza and Steel (2005)

issue is the fact that two third of taxpayers who itemized prior to the enactment of the TCJA ceased to afterwards, considerably limiting the data sample.

The other broader problem with relying on individual tax returns are their general unreliability. Previous studies have shown that tax returns often contain several inaccuracies, especially in terms of self-reported charitable donations by itemizing filers and many other pieces of self-reported information by the self-employed at large.[5] [6]

Methods Using Survey Data—

The main alternative to using publicly available tax return data is to survey donors themselves. There exist several household surveys that seek to quantify a variety of data points covered in tax returns while avoiding the bias associated with the returns themselves. Studies have shown, however, that these surveys often produce inaccurate results. In particular, itemizers tend to overstate their charitable giving, just as they do in their tax returns.[7] Furthering this point, Hurst, Erik, et al. state in their study *Are Household Surveys Like Tax Forms: Evidence from Income Underreporting of the Self-Employed*: "It is naive for researchers to take it for granted that individuals will provide unbiased information to household surveys when they are simultaneously providing distorted information to other administrative sources."[8]

Methods Using Matching Grants as RCTs—

Another alternative method used in the literature to identify how donations respond to incentives is the use of a matching grant campaign as a randomly controlled trial. For example, one sample of random donors is offered a one-to-one dollar match on a charitable donation, while another random sample is offered a two-to-one match. While in theory this provides the controlled experimental setup needed to produce unbiased results, in reality it does not serve as truly functional RCTs. The data show that matching grants have almost no effect at all on donor behavior, which is likely due to other factors involved in these campaigns creating confounding variables.[9]

D. Using State Tax Variation in a Difference in Difference Model

To mitigate the constraints and biases of these previously stated popularly used methods

[5] Scotchmer and Slemrod (1989)
[6] Joulfaian and Rider (2004)
[7] Kolm and Ythier (2006)
[8] Hurst et al. (2011)
[9] Karlan and List (2007)

of calculating elasticity, this study utilizes a difference in difference model centered around state income tax variation and data from medical charities' tax filings.

When trying to utilize the reported public donations that charities receive to discern how a change in tax incentives affected giving, an additional element of randomness is needed, as simply observing the change in donations over time cannot isolate the effect of the tax law. Differences in the pre-existing state income taxes create this random element, as they remain constant before and after a federal tax change and vary the overall tax incentive to donate across the states.[10]

As a hypothetical demonstration of this effect, consider two states A and B, with income tax rates of 0% and 10% respectively, and suppose the federal marginal income tax rate is 40%. For two identical itemizing donors who live in state A and B, the FDTC of the state A donor is \$0.60 and the FDTC of the state B donor is \$0.50. When new tax legislation reduces their federal marginal income tax rate from 40% to 30%, and both donors continue to itemize, the FDCT of the state A donor increases from \$0.60 to \$0.70 and the FDCT of the state B donor changes from \$0.50 to \$0.60. Thus, the donor in state A sees a ~14% relative decrease in their incentive to donate, while the donor in state B experiences a ~16% relative decrease.

This study identifies the FDTCs of a representative random sample of donors in each state and regresses the changes in FDTC caused by the TCJA against the log change in public donations received by charities by state to calculate a tac cost elasticity of charitable giving. This regression construction is detailed further in the methodology section.

E. The Tax Cuts and Jobs Act

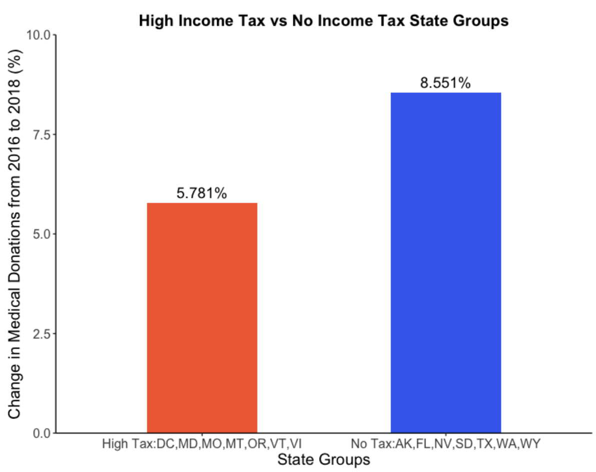
The Tax Cuts and Jobs Act of 2017 reduced the federal marginal income tax rates of most Americans. Additionally, and vitally, it dramatically reduced the incentives for tax filers to itemize their deductions by doubling the size of the standard deduction, creating a \$10,000 cap for the SALT deduction, and eliminating miscellaneous itemized deductions and casualty loss deductions altogether.[11] The combined effect of these changes caused the percentage of income tax filers in the US who itemize their deductions to fall from approximately 30% to just 10%[12], thus

[10] Feenberg (1987)
[11] S. 2254 — 115th Congress: Tax Cuts and Jobs Act.
[12] Gale et al. (2018)

drastically increasing the FDTC of those 20% of donors who no longer itemize.

As shown in Figure 1, the seven states with no state income tax (and thus a larger portion of their residents who did not itemize before the TCJA) saw a growth in medical donations of ~8.6% from 2016 to 2018. The seven states with the highest state income tax, and thus a larger relative decrease in incentive to donate due to a larger reduction in itemization, saw a smaller growth of ~5.8%.

FIGURE 1



Note: While both groups of states saw an increase in donations to medical charities, the high income tax states saw an increase that was over 40% lower relative to the no tax states.

It is worth noting that in both groups of states the total amount of money donated to medical charities increased. This is likely due to the many other notable economic and social factors also present at the time, rather than just the change in tax policy. The overall strong economy, especially as measured by stock market growth, may have made some more willing to increase charitable giving. Additionally, the politically tumultuous nature of the last few years may have led some to donate more to charity in general. More analysis on these other incentives and how they relate to the TCJA and this study is given in the discussion section below.

Figure 1 should not be interpreted as a causal quantification of the TCJA's effect on medical donations, but rather as a demonstration of how this effect is noticeable even without the controlled covariates of an OLS regression. This difference in donations received from medical charities in different states as caused by the TCJA is more robustly explored by the OLS regression and further analysis provided below.

II. Methodology

Described here is the difference in difference model used to calculate the causal effect of the TCJA on public donations to medical charities, the sources of data used, the calculation of key variables, and the regression model fitted. This particular method of estimating elasticity of giving is adapted from Nicolas Duquette's paper *Do Tax Incentives Affect Charitable Contributions? Evidence from Public Charities Reported Revenues*.

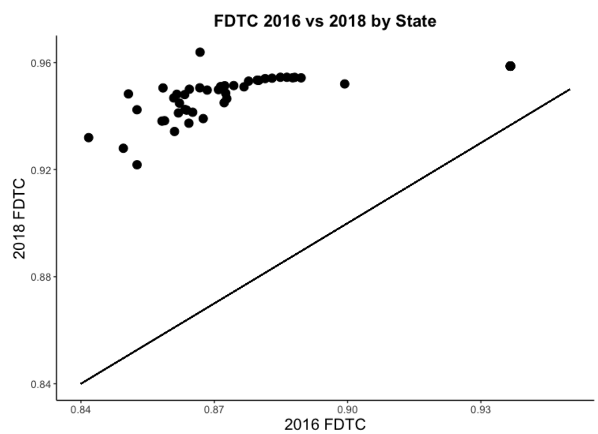
A. Difference in Difference Model –

By utilizing the differences in state income taxes, this study creates a dosed difference in difference model to isolate the effects of the TCJA on donation to medical charities. States with a higher state income tax, such as Maryland, have a larger incentive for their residents to itemize their returns. This effect accounts for the majority of the difference in FDTC between high and low tax states. Additionally, with a top marginal rate of 5.75%, donations to charities that are deducted from an individual Maryland resident's tax returns cost $0.0575 less per dollar than a donor from a state without its own income tax, such as Texas. This means that if both hypothetical donors face the same reduction in federal marginal tax rates, the effect on their incentive to donate is different. This difference is substantially larger if one stops itemizing their returns.

The variable this study uses that captured this difference is called first dollar tax cost of giving (FDTC), which is the average cost of donating one dollar for a particular state's donor. FDTC accounts for both changes in marginal tax rates at the state and federal level, as well as the change in a donor's decision to itemize. More detail on how this variable is calculated is given below.

Figure 2 represents the average FDTC of each state in the years 2016 and 2018. It shows a decrease in the broad spectrum of combined federal and state income tax rates across the board following the enactment of the TCJA. However, each state experienced a unique magnitude in this downward shift of income tax rate and overall incentive to donate. These differences in the percentage by which FDTC changed between states forms the "dosage" of the dosed difference in difference model.

FIGURE 2



Note: Each individual point represents a state's FDTC in the respective years, while the 45 degree line in the center shows hypothetical FDTCs in the absence of the TCJA

B. Data Sources –

Data used to construct the first dollar tax cost of giving comes from the IRS public use Statistics of Income (SOI) tax return files, while data on charity location and donations come from IRS Form 990 extracts. Headquarters location and name data for each charity came from The National Center for Charitable Statistics Data Archive. These data were merged with the 990-extract data, and will thus be referred to as one data source

IRS Form 990—

Filing an IRS Form 990 is required for any tax preferred organization, including any 501(c)(3). Larger charities file the standard Form 990, while smaller charities file the simplified Form 990-EZ. The vast majority of the charities included in this study file standard 990s, due to the large average size of a medical charity.

The information from these 990 extracts utilized in this study include EIN (charity identification number), annual public donation revenue, state, organization name, North American Industry Classification System (NAICS) code, and date of tax filing for the years 2016, 2017, and 2018.

SOI Public Use Files—

The public use SOI files contain tax return information from a nationally representative sample of 4,800 filers. These data are somewhat redacted to conceal filer identity, but include income, location, marital status, age, and over one hundred other variables used to calculate tax liability. Files from the year 2016 were used.

C. FDTC Variable Calculation –

In order to account for the impact that the TCJA had on a donor's first dollar tax cost of giving, this study calculates the log difference in FDTC from 2016 to 2018. This calculation begins with the SOI public use files from the IRS.

First, the SOI data, which includes 4,800 entries, is transformed using the following process. States are encoded from 1 to 51 (including Washington D.C.). The state of residence for every filer is changed to the same state code, creating an identical representative sample for each state. Total charitable contributions for each filer are then reduced to zero. This is repeated for every state, resulting in 51 tax return files. Next, a mirroring set of files is made, in which charitable contributions is set to $10. Then, this entire process is repeated for each state after the year has been changed to 2018 and all monetary variables are adjusted for inflation using the CPI. Once completed, there are a total of 204 files.

Each file is then run though the Taxpuf27 function in TAXSIM in order to calculate total tax liability. TAXSIM is a program that uses tax filer information as the input and produces total state and federal tax liability from any number of filers.[13] The total liability difference between the $0 donation and $10 donation files for each state in each year is then divided by ten to calculate the first dollar cost of giving. One minus the log difference between the 2016 and 2018 FDTC is calculated to create the final variable.

D. Use of First Dollar Tax Cost of Giving –

Several studies utilize a different method of estimating tax elasticity of charitable giving by using first dollar tax cost of giving as an instrumental variable for last dollar tax cost of giving. While last dollar cost is a theoretically better measure of tax incentives, as the marginal tax rate of a donor may change as a result of a donation, its use in this study neither feasible nor necessary.

Since we do not observe the individual donors for each charity, creating this instrumental variable model is not possible. Furthermore, in Duquette's 2016 study, on which this study's model is based, the same obstacle was encountered. In that study, the author created an estimated last dollar tax cost variable by adding data for hypothetical donations based on average donation amounts of the time. He then used FDTC as an instrumental variable in regression and found that the results were not significantly different from his original findings. Thus, it was determined that the bias created by using first dollar instead of last dollar tax cost is negligible.[14]

E. Form 990 Data Filtering –

Data from the IRS Form 990s were filtered the following ways prior to regression. After selecting for only organizations that filed as 501(c)(3)s, entries were further filtered to only include those that had NAICS subcodes beginning in 62, which indicates they operate in the health sector.[15] Charities that took in zero dollars in donations in any year were then removed, along with any charity not represented in all three years of interest and any charities with missing values in any relevant field. Charities that appeared multiple time in the 990 extract, which is the result of amended filings, were sorted such that only the most recent filings were included. Finally, manual filtering was performed to remove food banks that had mistakenly filed as medical charities.

[13] Feenberg and Coutts (1993)

[14] Duquette (2016)

[15] NAICS (2017)

F. Focus on Medical Charities –

This study utilizes a dosed difference in difference model that attempts to find a causal relationship between log difference in first dollar tax cost of giving in a respective state and changes in public donation revenues for charities in that state. As such, this study makes the critical assumption that the majority of a charity's donations come from instate donors. This is naturally untrue for many charities, especially those that operate across multiple states or otherwise interact with individuals in several states or countries. Nevertheless, this study takes many steps to ensure that it isolates as high a proportion of charities with mostly in-state donations as possible.

The largest step taken to achieve this goal is the narrowing of sample to include only medical charities. This group of charities consists mostly of local hospitals and clinics, which are assumed to receive most of their donations from instate. Focusing the sample on medical charities yields additional benefits: the quality of data from these charities, such as accuracy of filings and lack of missing fields in the 990 extracts, was higher than in any other group. This ensures the regression outcome is more accurate. Additionally, while this group of charities only represents a portion of the charitable work being done in the US, it is considered by many to be one of the most critical charitable sectors.

In addition to studying only medical charities, the regressions performed removed the 200, 300, and 400 highest grossing charities in terms of public donation revenue. These charities had substantially higher revenues than the average for the sample and may have collected most of these donations from out of state. Saint Jude's Children's Hospital and The Mayo Clinic are examples of such charities. These exclusions had only marginal effects on the elasticity of giving estimate.[16]

G. OLS Regression –

The relationship between charitable contributions and tax incentives can be written as the following equation:

$$(1)\ \ln\left(C_{i,t}\right) = \alpha_i + \gamma_t + \beta \ln\left(T_{i,t}\right) + \delta_s + \eta_{i,t}$$

Here, $C_{i,t}$ represents contributions to an individual charity in a given year, $T_{i,t}$ represents the tax incentives to give to that charity in the same given year. δ_s is a state fixed effect, α_i is a charity fixed effect, and γ_t

[16] The results of the regression performed with no charities cut from the sample is reported in Appendix Table 1

is a fixed year effect. $\eta_{i,t}$ represents the other factors influencing a donor's decision to donate to that charity in that year, such as political conditions and a variety of other economic incentives. This variable is normally distributed and has a mean of zero due to the charity fixed effect.[17]

Next, specifying Equation 1 for the year 2018, we have the following equation. The years 2016 and 2018 are abbreviated to 16 and 18, respectively.

(2) $\ln(C_{i,18}) = \alpha_i + \gamma_{18} + \beta \ln(T_{i,18}) + \delta_s + \eta_{i,18}$

Subtracting the same equation for the year 2016 from Equation 2, we have:

(3) $\ln(C_{i,18}) - \ln(C_{i,16}) = \alpha_i - \alpha_i + (\gamma_{18} - \gamma_{16}) + \beta\,[\ln(T_{i,18}) - \ln(T_{i,16})] + \delta_s + (\eta_{i,16} - \eta_{i,18})$

This variable β represents the causal effect of a change in tax incentives on the donations received by a specific charity. If we further develop the variable T into the tax change caused specifically by the TCJA, and specify the left hand side variable to include only changes in donations received from 2016 to 2018 for all applicable medical charities, we have:

(4) $\ln(C_{i,18}) - \ln(C_{i,16}) = (\gamma_{18} - \gamma_{16}) + \beta\,[\ln(FDTC_{s,18}) - \ln(FDTC_{s,16})] + (\mu_{i,18} - \mu_{i,16})$

Where i = charity, t = year, s = state, and $FDTC$ = first dollar tax cost of giving to charity. $\ln(C_{i,18}) - \ln(C_{i,16})$ is the log change in contributions received by a given medical charity i between 2018 and 2016, and $\ln(FDTC_{s,16} - FDTC_{s,18})$ represents the change in log mean tax price of giving (1- τ) from 2016-2018 in a given state s. The difference $\gamma_{2018} - \gamma_{2016}$ represents how much we predict donations to have changed between 2016 and 2018, had tax incentives not changed. The difference $\mu_{i,2018} - \mu_{i,2016}$ is normally distributed and has a mean of zero due to the properties of the normal distribution.[18]

[17] This equation is estimated for the years 2016 and 2018 in Appendix Table 2

[18] Since the charities observed in this study are organized by state, and the changes in donation revenue received by the charities within each state are not independently distributed, it is possible that the standard errors reported in Table 1 are not appropriate. This is because the treatment assignment in this model (change in FDTC) is directly correlated with the subgroups (states). Increases in donations seen by charities between 2016 and 2018 in one particular state may be, in part, due to independent statewide characteristics, which are by definition correlated with that state's change in FDTC. As a way of accounting for this, standard errors are clustered by state in Appendix Table 3, which produced an estimate for β not statistically significant at the 95% level but significant at the 90% level. This should be interpreted as an acknowledgement that, if there exist widespread, independent reasons within several states that caused changes in 2016 to 2018 donation behavior and weren't related to the TCJA, then the estimates of the effect of change in FDTC presented in Table 1 may be less significant than suggested.

III. Results

The regression as described above produced relatively large and highly statistically significant estimates for elasticity of medical giving. This implies that the TCJA caused a large reduction in donations to medical charities.

Table 1 show the results from the three main OLS regressions performed, which calculate an estimated tax cost elasticity of medical charitable giving. These estimates, which range from -3.61 to -3.55 are not statistically significantly different from one another. These main estimates should be interpreted as: for every one percent increase in the tax cost of giving for an individual donor, on average that donor will give 3.61 percent less to medical charities that year.

TABLE 1

	Excluding Top 200 Charities	Excluding Top 300 Charities	Excluding Top 400 Charities
Intercept	12.96382*** (0.06049)	12.93472*** (0.06013)	12.90469*** (0.05987)
Change in FDTC	-3.61794*** (0.77231)	-3.60450*** (0.76763)	-3.55475*** (0.76419)
n	16,482	16,282	16,082
R-Squared	0.0006278	0.0006309	0.000618

Notes: Dependent variable is log change in donation revenue from 2016 to 2018. Change in FDTC is the estimate of tax elasticity of charitable giving to medical charities. Standard errors are shown parenthetically under each estimate.

*** Significant at the 1 percent level.

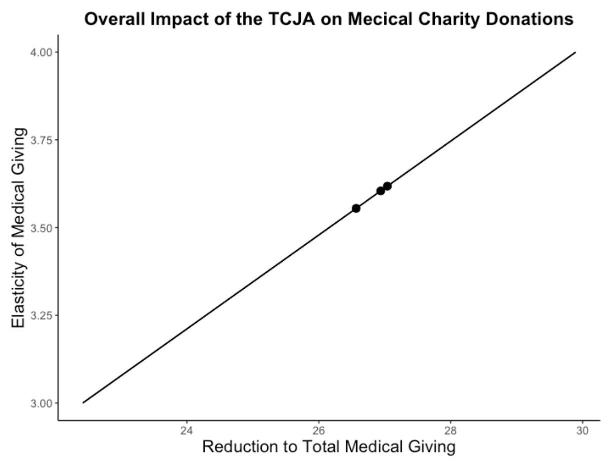
** Significant at the 5 percent level.

* Significant at the 10 percent level.

These elasticity estimates can be further utilized to calculate an overall reduction in potential medical donations for the year 2018. After the passage of the TCJA, American taxpayers saw their tax cost of giving increase by 7.47% on average. This figure incorporates both the increase due to higher marginal tax rates and, more importantly, lower rates of itemization.

Figure 3 shows the overall decrease in potential donation associated with each elasticity estimate presented in Table 1.

FIGURE 3



Note: The calculation this graph represents is the elasticity estimates from the previous table times 7.47%, which is the average national reduction in marginal tax rate. The regressions that cut the top 200, 300, and 400 medical charities in terms of annual revenue imply a total decrease in medical giving of 27.04%, 26.94%, and 26.57% respectively from 2016 to 2018.

These estimates of the elasticity of giving to medical charities imply a total decrease in potential giving of approximately 27 precent between the years 2016 and 2018, or roughly a 13% lower annual public donation total than would have happened without the passage of the TCJA.

IV. Discussion

The model used by this study requires a number of assumptions that may not be valid, which could lead to biased elasticity estimates. In this section, those biases are examined and shown to be non-impactful. Additionally, further explanation is given as to why alternative models were not employed.

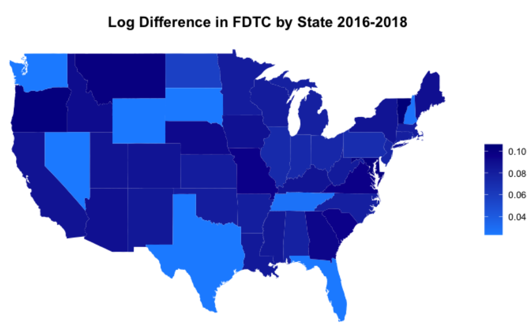
A. Addressing of Potential Bias –

There are several elements intrinsic to the design of this study that have the potential to introduce bias. Below is an analysis of some of the factors most likely to either skew the numerical value of the results or interfere with the causal interpretation of the TCJA's effect on donations. These factors are shown to not cause significant bias.

Geographic Bias—

It is possible that states with low changes and states with high changes in first dollar tax cost of giving are geographically proximate, thus introducing potential bias. This would be the case if, for example, the states with the highest differences were located along the coasts, thus potentially causing correlated variables like regional culture to become confounding. This would be the case if these cultural differences were responsible for a change in donation behavior between 2016 and 2018 and the states with said changes were correlated with FDTC. For example, if the New England states saw an increase in donation to medical charities due to some non TCJA related factor and those states all had large changes in FDTC. This is a relatively small concern, and as Figure 4 shows, there is no clear evidence to suggest that this is the case; log difference in first dollar tax cost of giving is randomly distributed across the states by geography.

FIGURE 4



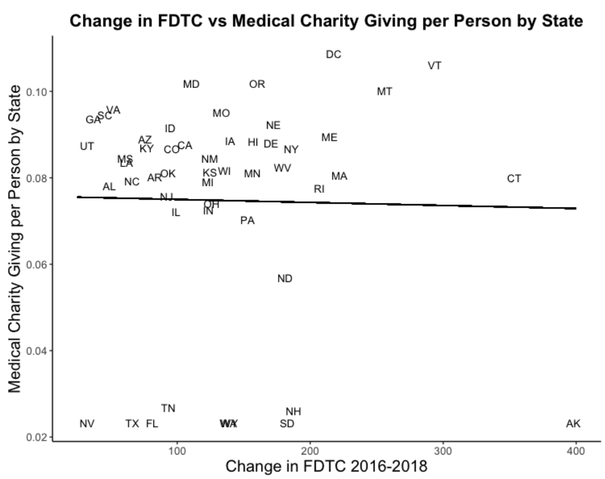
Note: Map showing geographic distribution of change in FDTC across the US. Darker blue corresponds to a higher difference in FDTC.

Giving Biases—

A change in average donation behavior between 2016 and 2018 caused by the TCJA in through a channel other than itemization incentives studied could also introduce bias. If the population of some states were already more interested in donating to medical charities than others before the TCJA, this difference could have been exacerbated by the passage of the law. Since other variables are controlled for, this would only be a problem if there was a correlation between states pre-disposed to donate more to medical charities and a higher change in FDTC.

As Figure 5 shows, this is not the case. There is no statistically significant correlation between FDTC and pre-TCJA per person giving to medical charities.

FIGURE 5



Note: The equation of the trendline is y=-7E-06x + 0.0757 and the R squared value is 0.0005. This scatterplot shows no obvious correlation between change in FDTC and pre-TCJA per capita giving.

B. Other Factors Effecting Donations –

As noted in the $\eta_{i,t}$ variable from Equation 1, and the overall increase positive donation trend seen in Figure 1, there were several other factors present that influenced an individual donor's decision to give money to medical charities between 2016 and 2018. Some of these reasons, such as heightened political awareness due to the social climate of the time, are reasonably assumed to be uncorrelated with state-specific TCJA-induced changes in FDTC. Other factors, however, such as the overall increased wealth levels seen across the country due to a strong stock market, cannot be wholly separated from the TCJA. If the TCJA caused an increase in stock prices, which made people richer overall, it could have created a wealth effect that raised donations to medical charities overall.

This being said, this wealth affect is accounted for on average in the $\gamma_{2018} - \gamma_{2016}$ portion of Equation 4. If the TCJA is to be considered as a whole, these wealth effects must be examined. However, since this study focuses on the price effect of tax cost on average donations, no assumptions are made about the wealth effects, as they are directly accounted for. Thus, they do not otherwise influence the results.

V. Future Work

It remains unknown why the medical sector has a heightened tax price elasticity of giving relative to other sectors. Both previous studies and this study's own preliminary research found that medical charities are the most tax sensitive group of non-profits, followed by education organizations. Reasons for this fact are however, up to this point, speculative. It is a possibility that borderline itemizing donors who were most directly impacted by the TCJA, i.e., those individuals with enough money to itemize but perhaps wouldn't be considered rich, favor medical and educational charities. It is also possible, however, that this apparent pattern is an artefact of the higher quality data available for medical and education charities. Both medical and educational charities tend to be larger, and thus file the regular IRS Form 990 instead of the substantially less detailed Form 990-EZ. Furthermore, it is also possible that due to some ingrained norms of institutional organization, tax forms filed by these organizations are more complete and have fewer errors or missing data points. It is possible that many other charitable sectors are just as tax sensitive, but the data are not robust enough to reveal this fact. Perhaps future studies could isolate the medical and educational sectors and compare them to the dozens of other types of charities to identify the cause of this calculated difference.

VI. Conclusion

By using a difference in difference model based on the changes in tax incentives to donate brought on by The Tax Cuts and Jobs Act of 2017, this study estimates a tax cost elasticity of giving to medical charities of approximately -3.6. This change in the after tax cost of giving is estimated to account for a 27% smaller donation rate change in medical giving than would have occurred without the tax change.

These findings are particularly relevant given what occurred in the years after the law was passed. Starting in early 2020, the Coronavirus pandemic put tremendous strain on the entire US healthcare system, including medical charities. Due to the sudden nature of the epidemic, the preparedness of the many hospitals and clinics tasked with caring for COVID patients and later administering the vaccine was highly influenced by the charitable donations they had received in the preceding years. By quantifying the tax cost elasticity of giving, this study has determined that medical charities saw a significant drop in potential donations because of the TCJA, which is likely to have impacted their functionality at the time of COVID's onset. With this added knowledge will hopefully come greater understanding of and deference to how income tax policy effects the vulnerable and essential medical charity sector.

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APPENDIX

APPENDIX TABLE 1— REGRESSION OF FULL SAMPLE OF MEDICAL CHARITIES

	Full Sample
Intercept	12.73204***
	(0.01820)
Change in FDTC	-3.73472***
	(0.81138)
N	16,682
R-squared	0.0004385

Notes: Dependent variable is log change in donation revenue from 2016 to 2018. Change in FDTC is the estimate of tax elasticity of charitable giving to medical charities. Standard errors are shown parenthetically under each estimate.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

APPENDIX TABLE 2— ESTIMATES OF EQUATION 1

	2016	2018
Intercept	9.2307***	9.1024***
	(0.6061)	(0.6161)
FDTC	-3.8873***	4.0740***
	(0.6874)	(0.6988)
N	16,682	16,682
R-squared	0.001767	0.001881

Notes: Dependent variable is log change in donation revenue from 2016 to 2018. Standard errors are shown parenthetically under each estimate.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

APPENDIX TABLE 3— REGRESSION WITH CLUSTERED STANDARD ERRORS BY STATE

	Estimate	t-stat	p-val (naïve-t)
Intercept	12.66***	221.70	<0.001
	(0.0571)		
Change in FDTC	-3.62*	-1.79	0.0791
	(2.0184)		

Notes: Dependent variable is log change in donation revenue from 2016 to 2018. Standard errors were clustered by state using the coef_test function with vocv = “CR1” in R’s clubSandwich package. Change in FDTC is the estimate of tax elasticity of charitable giving to medical charities. Standard errors are shown parenthetically under each estimate.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.