ESSAYS IN THE ECONOMICS OF ALTRUISTIC BEHAVIOR

A Dissertation

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
In partial fulfillment of the requirements for the degree of

DOCTORATE OF PHILOSOPHY

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August 2020

Major Subject: Economics

ABSTRACT

The economics of altruistic behavior, and specifically the economics of charitable giving, is a large and rich field of research. This is not without cause: charitable giving is a significant household decision. We contribute in several ways to better understanding this fundamental household financial decision.

Despite widespread interest, there is little systematic evidence on the relationship between income, wealth, and charitable giving. In Chapter II, we use the Panel Study of Income Dynamics (PSID) spanning 2001-2017 to provide descriptive statistics on this relationship. We find that, irrespective of specification, donative behavior increases with greater resources.

Charitable giving is also incentivized by the U.S. tax code. In Chapter III, we use the PSID to get up-to-date estimates the tax price elasticity of charitable giving. We find that households that always itemize are less sensitive to changes in the tax treatment of donations than households that switch itemizing status. We apply these results to the provisions of the Tax Cuts and Jobs Act of 2017, taking into account the marginal propensity to donate from the increase in disposable income expected for most households, and predict a ~3.5% decrease in total individual giving.

In Chapter IV, we apply this methodology and data to evaluate a hypothetical policy world where religious organizations (e.g. churches, mosques) lose their tax-exempt status. We document the poverty of reliable, available data to robustly answer the different dimensions of this question. Despite this, we roughly estimate a significant increase in churches' expenses alongside a 1.8% decrease in giving to religious organizations.

Chapter V focuses in on giving behavior to one specific cause type: disaster relief. We consider decisions made by a sample of Texan adults in two, lab-in-the-field, modified dictator games. Three decisions target different charitable organizations, all of which have a disaster-relief mission, but differ in the level of operation. A fourth targets an individual recipient who was a victim of a fire. Giving is significantly higher to national and local organizations compared to state. We find a higher propensity to donate and larger amount donated to the individual relative to all organizations. Subsequent analysis compares a number of demographic and attitudinal covariates with donations to specific charities.

DEDICATION

For my family and friend-family, who are my team.

No one accomplishes anything alone, and this is no exception.

ACKNOWLEDGEMENTS

In addition to my committee members and coauthors, I am grateful for valuable comments on these essays from Jeffrey Brown, Nic Duquette, Dan Hungerman, Judd Kessler, Wojciech Kopczuk, Benjamin M. Marx, Robert Moffitt, Jonathon Oxley, Harvey Rosen, Mark Ottoni-Wilhelm. Participants at the 2019 Science of Philanthropy Initiative and NBER Tax Policy and the Economy conferences for helpful feedback on Chapter II and III. Daniel Feenberg valuable insight into the NBER TAXSIM program and Mark Ottoni-Wilhelm into the Panel Study of Income Dynamics data. Thanks also go to Sheheryar Banuri, Tara Larson Brown, Haley Harwell and Ngoc Phan for invaluable research assistance in conducting the experiment in Chapter V.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professor Catherine Eckel and Professor Jonathan Meer and Professor Tim Gronberg of the Department of Economics and Professor Jane Sell of the Department of Sociology.

The data analyzed for Chapter IV was provided by Professor Catherine Eckel of the Department of Economics and Professor Rick Wilson of the Rice University Department of Political Science. All other work for the dissertation was completed by the student, in collaboration with Catherine Eckel, Jonathan Meer, and Rick Wilson.

Funding Sources

Graduate study was supported by an assistantship from Texas A&M University. The study conducted in Chapter V was funded by the National Science Foundation (SES 0938090) and the Department of Homeland Security Center of Excellence for Natural Disasters, Coastal Infrastructure, and Emergency Management. Its contents are solely the responsibility of the authors and do not represent the official views of either agency.

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CHAPTER I

INTRODUCTION

Research on charitable giving can be broadly categorized into four approaches: individual economic decision-making; strategic interactions between actors (e.g. donors, charities, and the government); social exchanges between solicitors and potential donors; and empathic, moral, and cultural motives for giving (Andreoni and Payne, 2013). This set of essays addresses research questions in the first and last of these four categories.

In Chapter II, we estimate the relationship between income, wealth, and charitable giving; in Chapter III, we calculate updated tax price elasticities of giving and apply those estimates to predict how the Tax Cuts and Jobs Act of 2017 will affect charitable donations, while accounting for income and wealth utilizing what is learned in Chapter II; in Chapter IV, we evaluate the implications of a hypothetical policy – the removal of tax exemption for religious organizations – using the tools developed in Chapter III; and in Chapter V, we use a lab-in-the-field experiment to understand how donors consider giving to different geographic levels of disaster relief efforts.

It is helpful to begin with a model of charitable giving to frame this analysis. We first consider charitable giving as both a public and private good (Andreoni, 1989). The original model of pure altruism (most thoroughly treated by Bergstrom *et al.* (1986)) considers giving only as it impacts the production of a public good. An important result of this model is that others' gifts are perfect substitutes for one's own (Andreoni, 2006). This means that if person j donates an additional dollar then person i will decrease her giving by one dollar. However, as Andreoni (2006) notes, this does not sufficiently explain observed charitable giving behavior.

Instead, we use as a starting point the impure altruism ("warm-glow giving") model (Andreoni, 1989; 1990). This model allows for an agent's utility to be a function of not only her consumption and the total production of the public good (as in the pure altruism model), but also her own private contribution to the public good. Put simply, people also get utility from being the person donating, not just from the overall level of the amount raised.

Following Andreoni (1990). Let individual i have utility function:

$$u_i = u_i(C_i, G, G_i)$$

where C_i and G_i are the consumption and giving, respectively, of individual i and G is aggregate giving to the public good. If we let $G_{-i} = \sum_{j \neq i} G_j$, i.e. the gifts of every person except individual i to the public good, then we can solve the following optimization problem to obtain the supply of donations:

$$\max_{C_i,\ G_i,\ G} \ u_i(C_i, G, G_i)$$

$$s.t.\ \ C_i + G_i = Y_i$$

$$G_{-i} + G_i = G$$

where Y_i is the income of individual i. Both pure and impure altruism models assume that C_i and G_i are normal goods, meaning that as Y_i increases so does agent i's consumption of C_i and G_i. We test this assumption in Chapter II by looking at the impact of income and wealth on charitable giving, but for now, following the literature, we take this as given and look at the implications of the model.

Solving the individual maximization problem, an important distinction from the pure altruism model arises: others' gifts are now imperfect substitutes for individual i's giving, i.e. there is incomplete crowd out. More plainly, this means that an agent does not necessarily respond to the increased giving of others by decreasing her own giving by an offsetting amount; she cares about where the gift comes from, especially that *she* contributes G_i. The degree to which donations are crowded out is determined by the relative strength of warm-glow and altruistic motives for each agent. Further, the impure altruism model implies that as the number of individuals in the economy increases, giving becomes increasingly like a private good: warm-glow dominates altruistic determinants of utility.

This is important in the context of our data for Chapters II to IV where there are many people in the economy and many donors.[1] Giving by one agent should have virtually no crowding-out effect on the giving of another agent, on average, leaving an increase in income and wealth to more strongly mediate donation activity. In addition, it is important to note that for Chapters II to IV, we separate income and wealth in analysis and analyze their fluctuations over time. The standard impure altruism model is a single period optimization problem; as such, it does not treat income and wealth separately (i.e. Y_i is just individual i's income) or consider intertemporal budgets. The methodology used in Chapters II to IV exploits variation in income, wealth, and giving over time and across households, making this model a useful but incomplete baseline for analysis. That said, the model's main conclusions discussed above – about warm-glow giving dominating and crowding-out being minimal – still hold if we instead consider Y_i to be the sum of available resources (i.e. income plus wealth).

[1] In Chapter V, we look at how personal beliefs about the relative effectiveness of different types of organizations affect donation decisions. We do not model this explicitly in a utility-maximization context as above nor do we have the context of many donors in the economy as in Chapters II to IV. We can imagine that the level of an organization's operation is a determinant in the amount of utility a gift generates. Our hypotheses and resulting estimation strategy for this are discussed in the chapter.

It is important to note that the predictions of the impure altruism model only hold under conditions of perfect information about the "quality" of the public good. In the absence of perfect information, it is possible that giving by others – individuals in the economy or the government in the form of grants – could serve as a signal of the quality of the public good (e.g. charity) and encourage, or "crowd in", donations by an individual (List, 2011). There has been a significant amount of research conducted that supports this idea (Andreoni and Payne, 2003; Gottfried, 2008).

For something more fitting to the context of our data, we turn to the dynamic model of giving behavior outlined in Auten, Sieg, and Clotfelter (2002) (ASC02). This model provides the basis for analysis in Chapter III (and therefore Chapter IV) by introducing income taxation. Following ASC02, and because of the conclusions from the impure altruism model, we simplify the model by treating giving solely as a private good. ASC02 represents an agent's preferences with a time-separable expected utility function and a constant discount factor, β:

$$E_t\left\{\sum_{s=t}^{\infty}\beta^{s-t}U_i(G_{is},C_{is})\right\}$$

where $U_i(G_{is},C_{is})$ is agent i's utility in period s taking elements of her giving (G_{is}) and consumption (C_{is}). This is subject to an intertemporal budget constraint in each period t:

$$C_{it}+G_{it}+W_{i,t+1}=(1+r_{it})W_{it}+Y_{it}-T_t(r_{it}W_{it},Y_{it},G_{it})$$

Where W_{it} denotes agent i's wealth at the beginning of time t, r_{it} is the interest rate faced by agent i, and Y_{it} is income. $T_t(\cdot)$ is the tax burden for i in t, which is a function of income, giving, and interest gained on wealth. ASC02 does not explicitly specify the form of $T_t(\cdot)$, but following the vast related literature we model the tax treatment of income and giving as $(Y_{it}-G_{it})\tau_{it}$, where τ_{it} is the marginal tax rate for agent i in period t. This means that income less giving is the amount taxable by the government. For generality, we do not specify the tax treatment of wealth. We can then rewrite the budget constraint as:

$$C_{it} + G_{it} + W_{i,t+1} = (1 + r_{it})W_{it} + Y_{it} - (Y_{it} - G_{it})\tau_{it} - T_t(r_{it}W_{it})$$

Combing like terms yields:

$$C_{it} + (1 - \tau_{it})G_{it} + W_{i,t+1} = (1 + r_{it})W_{it} + (1 - \tau_{it})Y_{it} - T_t(r_{it}W_{it})$$

Solving the utility maximization problem produces a within-period optimal allocation of resources rule:

$$(1 - \tau_{it})\frac{\partial U_i}{\partial C_{it}} = \frac{\partial U_i}{\partial G_{it}}$$

In words, this means that in each period an agent equates her marginal utility from giving and marginal utility from consumption, mediated by what is commonly called the “tax price of giving” $P_{it} = 1 - \tau_{it}$. This equation shows the price of giving an additional dollar that agent i faces in period t: each dollar donated is a dollar less of income that is taxed, which reduces the tax bill by the marginal tax rate on that dollar, τ_{it}. If $P_{it} = 0$ (say, from a marginal tax rate of zero), then the utility-maximizing agent consumes and donates up to the point where her marginal utilities are equal.

This model provides a useful framework for how to think about giving when it is subsidized by the government through the tax system, as is the case in many countries (Andreoni, 2006). However, empirically estimating this optimal decision rule is computationally difficult. Similar to others in this empirical literature, we instead analyze a linearized version of the above model:

$$g_{it} = \beta_0 + \beta_1 p_{it} + \beta_2 Y_{it} + \beta_3 W_{it} + \beta_4 \boldsymbol{X_{it}} + u_i + e_{it}$$

where g_{it} and p_{it} are the logarithms of donations and price, respectively; Y_{it} and W_{it} are controls for income and wealth; $\boldsymbol{X_{it}}$ is a vector of time-varying household characteristics; u_i is a time-invariant individual fixed effect; and e_{it} is the time-varying error term. We discuss the exact specification of this equation in more detail in Chapter III.

Shortcomings of the model

The above discussion for both the impure altruism and dynamic donation decision models are based on utility maximization by an individual. However, our data in Chapters II to IV are at the household level. This is not problematic if households behave as a single utility maximizer, which Becker (1974) shows would occur under a "benevolent head" of the house. This is not how households really behave (Andreoni *et al.*, 2003). Household bargaining models better capture observed behavior, and within-family bargains are mediated by several characteristics such as relative incomes, demographics, and more (Andreoni *et al.*, 2003). Since our model does not account for household bargaining, the conclusions may not accurately translate into our analysis; however, the model's implications which we are instead in are fairly basic and should hold up when translating from individual agents to households.

Most models require simplifications for some tractability. We simplify here by omitting different types of giving (e.g. volunteering, bequest, in-kind). This does not allow for directly estimating the substitutability of different types of giving, which might be especially important when comparing households across income and wealth levels. Such an "altruism budget" is discussed in greater detail in Gee and Meer (2019).

Removing pure altruism from our model simplifies the dynamic donation decision problem, but necessarily abstracts away from reality. It may be the case that a potential donor does care about the overall level of the public good as well as her own contribution. It may also be the case that warm-glow extends to involuntary donations via taxation (Andreoni 2006) if, for example, people get some utility from "contributing" to a public good through taxes paid to the government which then provides a service or gives a grant to a nonprofit. In this instance private giving could be only partially crowded-out in the presence of the tax subsidy described above. This is discussed to a degree in Ottoni-Wilhelm *et al.* (2017) and Hungerman and Ottoni-Wilhlem (2018). Eckel, Grossman, and Johnston (2005) find in a lab experiment that "taxation" almost completely crowded-out giving. For our purposes, the simplification is both necessary and sufficient for analysis on the data we have available and the research questions we seek to answer.

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CHAPTER II

GIVING ACROSS THE INCOME AND WEALTH DISTRIBUTIONS[2]

1. Introduction

The relationship between income, wealth, and charitable giving is of significant policy and popular interest, yet there is surprisingly little systematic evidence on the topic. While the press tends to highlight findings that suggest that the well-off are stingy (see, among many others, Grewal, 2012, and Young, 2017), the claims are questionable due to misuse of data, incomplete controls, inappropriate empirical specifications, and a lack of accounting for the influence of outliers.[3]

Using the Panel Study of Income Dynamics, we provide the most rigorous documentation of these relationships to date. We estimate the relationship between pre-tax income, wealth, and charitable giving over three measures of generosity: the likelihood of giving, the amount given, and the percent of income given. We report means, estimates using ordinary least squares with a rich set of household demographic controls, as well as estimates with household fixed effects. Our statistical models take care to mitigate the potentially misleading impact of outliers by winsorizing households' percent of income given. This allows us to simultaneously retain the full sample while

[2] Previously published with J. Meer in *NBER Working Paper 27076*, NBER, Cambridge, MA.
[3] As an example, Stern (2013) documents the alleged miserliness of the rich, as measured by the percent of income given, using analysis from the Chronicle of Philanthropy discussed in Gipple and Gose (2012). However, that study was based on data from the Internal Revenue Service, for households that itemize their giving. Tax-filing units with incomes below $50,000 were not included, comprising nearly two-thirds of households. Thus, referring to giving by the "poor" is misleading. More importantly, though, itemizing one's deductions is an endogenous decision. At the lower levels of the income range in the study, only about half of tax returns were itemized, while at higher levels, nearly all returns were. Almost by definition, those who itemize despite lower incomes have higher levels of charitable giving; otherwise, they would not itemize. Further, changes to the tax code under the Tax Cuts and Jobs Acts of 2017 will significantly reduce the number of households that itemize, making tax data even more problematic for examining charitable giving (Meer and Priday, 2019).

limiting the degree to which outliers can skew estimation results. While the PSID undersamples very-high-income households, it provides the most complete view of charitable giving across the income distribution, and includes data on wealth, religiosity, and a number of other important correlates of giving that are rarely present in other data.[4]

We find that, irrespective of the specification, higher-income and higher-wealth individuals are substantially more likely to make donations to charity, and give significantly more. Once outliers are properly accounted for, the relationship between the percent of income given and income or wealth is generally flat. We also analyze data from the Internal Revenue Service Statistics of Income, and find that the very-highest-income individuals tend to give the most as a percent of their income.

One common finding in the literature is the "U-shaped" giving curve: the average proportion of income donated is largest at the lowest and highest parts of the income distribution, while middle-income groups give the smallest proportion of their income. For example, Clotfelter and Steuerle (1981) use IRS tax return data and find a U-shaped curve, which is later corroborated with a panel of tax filers by Auten, Clotfelter, Schmalbeck (2000), though only with mean, not median, giving.[5] However, there is no consensus on this point. Wiepking (2007) documents the relationship between income and giving in the Netherlands, finding a flat relationship for the likelihood of giving and a negative one on the percent of income given. Schervish and Havens (1995a, 1995b) estimate that the giving curve is essentially flat when considering the full sample,

4 Wealth, in particular, is an important determinant of giving (James and Sharpe, 2007), particularly at the end-of-life (Bakija, Gale, and Slemrod, 2003; Meer and Rosen, 2013). Households may give not just out of income, but from existing wealth. As we show below, a good deal of the ostensibly higher giving levels by low-income households are in fact driven by those with high levels of wealth.

5 Few studies use panel data, and tax return data must be limited to those who itemize in every year. Rooney, Wilhelm, Wang, and Han (2019) show that the pattern of charitable giving across individuals when using a single year (or repeated cross-section) can be misleading.

not just those who donated a positive amount. James and Sharpe (2007) argue that selection bias drives the Schervish and Havens results. They find a U-shaped curve but note that it is not a valid description of the typical household within each income level: older "low-income" donors with higher wealth are responsible for the higher mean giving at the bottom of the income distribution. Importantly, other than James and Sharpe (2007), the effect of outliers has largely been ignored in this literature which, as we show below, leads to incorrect inference.[6]

Experiments, both in the lab and the field, have tackled this question as well. Andreoni, Nikiforakis, and Stoop (2017) summarize the literature on the relationship between prosocial behavior and income and test it by misdelivering envelopes in higher and lower resource neighborhoods. They vary the amount of money in the envelope and the ease with which the false recipient can retain it, and find that the rich are more than twice as likely to return the envelope as the poor. However, they argue that these results reflect different financial pressure and marginal utility of income, and that social preferences are in fact similar. Lab experiments are limited in the external validity of their results, as they rely either on the existing (and endogenous) level of resources of the subjects (Blanco and Dalton, 2019), or differences in "income" of just a few dollars created during the experiment (Duquette and Hargaden, 2019).

But there is a broader set of questions underlying this discussion: what is generosity, and how should it be measured?[7] Even taking a limited view – primarily for data-availability reasons – that generosity is measured by donations of money, the metric remains unclear. Is it the likelihood

[6] Duffy *et al*. (2015) use the 2001-2009 waves of the PSID to look at how income and wealth affect giving, with special attention given to directly comparing the PSID to James and Sharpe (2007).

[7] Gee and Meer (2019) discuss a number of related issues surrounding the notion of an "altruism budget." Lilley and Slonim (2014) and Brown *et al.* (2019) analyze the substitution between gifts of time and money.

of making any donation at all? The amount given? The amount given as a share of one's income? Of one's total resources, measured as wealth or permanent income? Over what period of time?

Ultimately, the question of what it means to be generous is philosophical and deeply normative. Whether one believes that the consequences of behavior (that is, observed giving) determines this state, or whether underlying intentions are more important (as Andreoni, Nikiforakis, and Stoop, 2017, do) is a personal matter. We strive to provide a set of facts about the empirical relationship between income, wealth, and giving, and leave it to the reader to draw his or her own conclusions.

Different empirical approaches provide insight into very different questions. A simple comparison of means (or medians) across the income and wealth distribution shows the most straightforward relationship between resources and giving, but compares people who face very different circumstances and are at different stages of life. That is, much of the observed relationship may be due to other factors that are correlated with both income (or wealth) and giving, so this approach shows only whether the sorts of people who have more money are the sorts of people who donate more. Ordinary least squares estimates examine the relationship conditioned on the effect of these factors, purporting to measure the effect of resources on giving, holding all else equal. But *unobserved* differences between people might still be driving the relationship. Using the panel nature of the PSID and including household fixed effects accounts for time-invariant characteristics, like altruism, and allows us to estimate how changes in income or wealth relate to changes in donative behavior, taking into account both observed and unobserved individual characteristics. This approach comes closest to answering how a household's charitable giving changes when it has more resources. However, as we detail below, even these results should not be viewed as completely causal.

2. Data and Specification

2.1 Data

The Panel Study of Income Dynamics (PSID) is a biennial household survey that collects information from the previous year on wealth, income, and a rich set of individual and household characteristics. The Center on Philanthropy Panel Study (COPPS), a PSID module begun in 2001, includes data on charitable giving to religious entities and ten categories of secular charities. We aggregate household donations for our primary analysis and explore possible differences in giving to religious and secular causes later.

The PSID is especially advantageous for analyzing charitable activity. Wilhelm (2006) shows that the data are superior to other surveys in coverage of charitable giving and compare well to tax return data below relatively high levels of income. Tax return data cover high earners – who constitute a large portion of charitable giving – and have higher precision; however, filers only appear in the data if they itemize contributions. This effectively results in a sample selected for higher income levels, precluding estimation across the broader income distribution. Recent changes in the tax code have dramatically reduced the number of households that itemize, limiting the value of these data moving forward (Meer and Priday, 2019). Tax return data also do not disaggregate giving by charity type. Further, data on wealth are not available on tax returns, although wealth is an important determinant of donative behavior (Bakija and Heim, 2011; James and Sharpe, 2007). Below, we show that wealth is important to consider when estimating giving behavior across all levels of the income distribution, not just high earners.

We use nine waves of the PSID spanning 2001–2017, representing every other calendar year from 2000 to 2016. The raw sample consists of 76,834 observations across 16,148 households. We remove observations with negative income (50) as well as the 2017 Immigrant Refresher (452) and the Survey of Economic Opportunity low-income oversample (23,199).[8] This leaves us with a final sample of 53,133 observations over 10,665 households. Across all household-years, 60 percent of households report making a donation. Conditional on making a donation, the mean (median) gift is $2,749 ($1,000) in 2018 dollars. The mean (median) income of our sample is $91,646 ($67,620); the mean (median) wealth is $356,082 ($71,400).[9] Table 1 contains the full set of summary statistics.

We examine three outcomes: the probability of giving, the log amount donated, and the percent of income donated, focusing on the first two. Outliers pose a particular problem when comparing the percent of income given across income levels. James and Sharpe (2007) show that the U-shaped giving curve is almost entirely driven by a small number of outliers at the bottom of the income distribution. These are often elderly households with high levels of wealth but low income. Non-elderly households with transitorily low income, perhaps through business losses,

[8] The immigrant refresher added new households to the panel beginning in 2017 to ensure the data remain reflective of the current demographic composition of the country. We omit this group as they appear in only one year of our data. The SEO subsample was included in the PSID to allow researchers to focus on low-income households. Including it in our analysis would oversample the bottom of the income distribution, skew bin specifications, and likely bias results. Given that the panel is nationally representative without the oversample, we opt to simplify analysis by removing these households instead of weighting the data.

[9] The PSID defines "family income" as the sum of taxable, transfer, and social security income for all family unit members. Wealth is the sum of a household's imputed business and farm equity, transaction accounts, value of debt other than main home mortgage or vehicle loans, home equity, other real estate equity, stock equity, vehicle equity, IRAs, and other assets.

may maintain giving behavior of other, higher-income years. Such "low-income" donors can distort means, as we show below. Controlling for wealth and age helps mitigate this problem but is not sufficient: outliers may still disproportionately skew means and mislead inference.

Table 1: Summary Statistics

	Mean	Median	Min	Max
Likelihood of giving	60.29%		0	1
Amount given	$1,658	$245	$0	$722,505
Winsorized at 20%	$1,576	$241	$0	$129,390
Amount given, conditional	$2,749	$1,000	$1	$722,505
Percent of income given	3.29%	0.32%	0%	369%
Winsorized at 10%	1.52%	0.32%	0%	10%
Winsorized at 20%	1.65%	0.32%	0%	20%
Winsorized at 30%	1.78%	0.32%	0%	30%
Family Income	$91,646	$67,620	$0	$7,391,006
Wealth	$356,082	$71,400	-$3,374,988	$117,649,300
Age	47		16	104
Retired	14.69%		0	1
Disabled	3.49%		0	1
Married	55.57%		0	1
Health of HOH				
Excellent	20.26%		0	1
Very good	35.41%		0	1
Good (or worse)	44.33%		0	1
Number of children	0.75	0	0	11
Catholic	24.48%		0	1
Protestant	53.96%		0	1
Jewish	2.63%		0	1
Other	2.93%		0	1
Atheist/Agnostic	15.98%		0	1
Years of education	13.38	13	0	17
African American	9.56%		0	1
Hispanic	9.73%		0	1
Housing price index	$338,939	$300,590	$148,460	$807,040

James and Sharpe (2007) address this by simply removing outliers with giving above a threshold percent of income. However, this introduces selection bias that is especially problematic when utilizing panel data; removing a household's observation in one year changes within-household estimation. Instead, we winsorize the percent of income given, a not-uncommon approach in other fields but relatively novel in charitable giving (Eckel, Herberich, and Meer, 2018). We cap the percent of household family income donated at 20 percent: any household-year observations donating more than that are assigned a value of 20 percent for percent of income given, while all other observations remain unchanged. We also generate the winsorized amount given by restricting the maximum amount donated by a household-year to be 20 percent of income.[10] These approaches allow us to retain all observations while limiting the disproportionate impact of outliers on intensive margin outcomes. Table 2 compares winsorized outcomes to their non-winsorized counterparts across income quantiles. While about 6 percent of the observations in the bottom income ventile are affected by winsorizing at 20 percent of income, this is sufficient to reduce the mean percent of income given by a factor of 16.

2.2 Specification

We divide family income and wealth into bins for analysis. Income is broken down into evenly-sized ventiles. Because there are a number of observations with negative or zero wealth (7,346 and 1,650, respectively), we create separate bins for each of these and divide all positive wealth into twenty evenly-sized bins, resulting in twenty-two wealth bins. Table 3 lists the range of the income and wealth bins.

[10] For robustness, we consider 10%, 20%, and 30% winsorization when analyzing the percent of income given. The log winsorized amount given uses a 20% winsor for all analysis.

Table 2: Income and Wealth Bin Ranges

	Income (in thousands)			Wealth (in thousands)		
Bin	Min – Max	Mean	Median	Min – Max	Mean	Median
1	0 - 11.2	6.1	7	-3,375 - 0	-41.0	-18.0
2	11.2 - 17.9	14.7	14.8	0	0.0	0.0
3	17.9 - 24	21	21	0 - 2.3	1.0	1.1
4	24 - 30.2	27.1	27.1	2.3 - 5.6	3.8	3.8
5	30.2 - 36	33.1	33.1	5.6 - 10.5	7.9	7.8
6	36 - 41.8	38.9	38.8	10.5 - 17.5	13.8	13.7
7	41.8 - 47.6	44.7	44.7	17.6 - 27	22.1	22.1
8	47.6 - 53.7	50.7	50.7	27 - 38.7	32.6	32.5
9	53.8 - 60.4	57.1	57.1	38.8 - 54.1	46.1	46.1
10	60.4 - 67.6	63.9	63.8	54.1 - 72.4	62.8	62.6
11	67.6 - 74.9	71.1	71	72.5 - 94.7	83.4	83.2
12	74.9 - 83.0	78.8	78.8	94.8 - 120	107.2	106.6
13	83.1 - 91.7	87.3	87.3	120 - 150.6	135.2	134.6
14	91.7 - 102.2	96.8	96.7	150.7 - 189.6	169.3	168.9
15	102.2 - 113.6	107.6	107.4	189.6 - 239.4	213.2	212.8
16	113.6 - 128.2	120.5	120.4	239.4 - 301	269	268.9
17	128.2 - 147.6	137.4	137.3	301 - 380.1	338.7	337.5
18	147.6 - 176.2	160.9	160.3	380.1 - 492.8	433.3	431.7
19	176.2 - 233.4	200.4	198.4	492.9 - 662.9	573.9	571.8
20	233.4 - 7,391	414.4	307.1	662.9 - 957.4	793.9	783.9
21				957.6 - 1,628	1,228.6	1,191.4
22				1,628 - 117,649	4,174.6	2,590

Discretizing income and wealth into bins reduces the effect of outliers in estimation without imposing a functional form on the relationship. However, using bins means that marginal effects measure movements across the income or wealth distribution, rather than the change from an additional dollar of income or wealth.

Table 3: Effects of Winsorizing, by Income Bin

Income Bin	Mean Percent of Income Given	10% Winsor		20% Winsor		30% Winsor	
		Mean	% Affected	Mean	% Affected	Mean	% Affected
1	33.60	1.30	7.91	2.01	5.69	2.56	4.33
2	1.82	1.12	4.78	1.43	2.26	1.58	0.87
3	2.07	1.46	5.69	1.76	1.58	1.87	0.75
4	1.75	1.32	4.40	1.54	1.05	1.62	0.57
5	1.94	1.33	4.29	1.54	0.94	1.60	0.38
6	1.79	1.34	4.22	1.57	1.01	1.65	0.64
7	1.65	1.33	3.84	1.50	0.90	1.56	0.49
8	1.76	1.50	4.46	1.67	0.57	1.70	0.23
9	1.72	1.50	4.17	1.67	0.49	1.69	0.26
10	1.79	1.55	3.99	1.73	0.68	1.76	0.23
11	1.76	1.59	4.17	1.73	0.34	1.75	0.11
12	1.82	1.58	3.69	1.69	0.34	1.71	0.19
13	1.72	1.59	3.01	1.70	0.38	1.72	0.04
14	1.77	1.63	3.35	1.75	0.30	1.76	0.08
15	1.82	1.66	3.65	1.78	0.30	1.81	0.19
16	1.99	1.73	3.47	1.86	0.60	1.90	0.41
17	1.83	1.74	2.82	1.82	0.19	1.83	0.08
18	1.96	1.77	3.28	1.89	0.45	1.93	0.30
19	2.04	1.78	2.82	1.89	0.45	1.92	0.19
20	1.71	1.60	2.18	1.69	0.34	1.71	0.04

There are well-documented determinants of giving behavior including age, gender, education, and race (Bekkers and Wiepking, 2011). We include controls for these characteristics, as well as marital status, retirement and disability status, self-reported health, and religious affiliation; number of children, a housing price index and its quadratic; as well as state and year effects.[11]

[11] Time-invariant characteristics are excluded in fixed effects specifications. Housing price and its quadratic are included to take into account the macroeconomic environment (List and Peysakhovich, 2011; Meer, Miller, Wulfsberg, 2017).

Addressing corner solutions – that is, non-donors – is a classic problem in the charitable giving literature. The Tobit is frequently used to account for this problem. However, this model suffers from tractability problems in the presence of fixed effects, is likely not appropriate when zeroes arise from corner solutions rather than true data censoring, and constrains the marginal effects on the extensive and intensive margins to be proportional to each other. This last issue is particularly problematic when considering the impact of, say, income, which may have very different impacts – possibly of opposite signs – on the likelihood of making a donation and the amount given.

We follow a more recent trend in the literature and treat giving as a two-step process: a household first decides if they will give, then, if so, how much they will give. Using ordinary least squares (OLS) and fixed effects (FE), we estimate the impact of income and wealth on the extensive and intensive margins of giving, then combine the results to find marginal effects on the unconditional amount given.[12] Standard errors are clustered at the household level in all specifications.

It is important to note that OLS and FE regressions answer different questions. Marginal effects from OLS give the impact on giving of moving across the income and wealth distributions, holding all observable characteristics equal. However, unobservable factors – particularly altruism – are likely to vary across these distributions, making it difficult to view these results as causal. If, for example, the types of people who hold large amounts of wealth tend to be less generous, even taking into account observable characteristics, then the giving-wealth gradient will be negative; it

[12] See Huck and Rasul (2011) and Meer (2011) for more discussion on the use of this specification for estimates of charitable giving responses. Wilhelm (2008) compares the Tobit to other specifications for charitable giving estimation.

would be incorrect, however, to conclude that higher levels of wealth *makes* people less generous. These specifications, therefore, are better suited to shed light on whether people who have or earn more money tend to be more or less generous than those who are observationally similar, but who have less money.

Fixed effects estimates hold time-invariant characteristics, like innate altruism or permanent income, fixed; that is, they measure how within-household changes in income or wealth impact within-household changes in giving. These estimates are more suited to answer questions about whether people become more or less generous as they acquire more money, and the marginal propensity to donate out of income or wealth. With controls for wealth and (implicitly) permanent income, these should also be viewed as the propensity to donate out of *transitory* income.

However, these fixed effects estimates require a nontrivial assumption to be taken as causal, namely, that *changes* in unobserved factors are uncorrelated with financial resources and giving. For instance, if a manager becomes more willing to help others both in her work and personal life, we might observe that she receives a pay increase and that her charitable giving increases. We would mistakenly conclude that the former causes the latter, even though both were caused by the change in her attitude and behavior. As such, even fixed effects estimates cannot be viewed as being a fully causal accounting of the relationship between income, wealth, and giving. To estimate a causal relationship in a compelling way, one would need random (or as-good-as-random) changes in income and wealth that are completely unrelated to individuals' own choices and (unobservable) attributes. Only then could we be assured of observing a causal impact on giving. Needless to say, it is quite difficult to imagine such circumstances. Further, there is evidence that giving behavior varies by the type of income shock (Drouvelis, Isen, and Marx, 2019); varying individuals' labor income or financial assets at random seems even more far-fetched than observing windfall gains at a large scale.

2.3 Limitations

The PSID has very few observations on high-income households, which make up the majority of donations and likely behave differently than households in our sample; we cannot directly infer the effects on their generosity using our results.[13] Tax filing units with earnings over $2 million made $63 billion in deductible contributions in 2016, or about 30 percent of the total, despite making up about 0.1 percent of the population (IRS, 2018). But there are only two observations with income above that level in the PSID in that year.

Additionally, the PSID samples households every two years and therefore depends on a respondent's ability to recall information from the previous year. Respondents may lie or forget about their income, wealth, or charitable donations, though Wilhelm (2006) argues the PSID is reliable and superior to other survey data in this respect. The rising popularity of donor-advised funds means people may shift charitable giving across years (Andreoni, 2018), which might be missed in our biennial data. Our data also covers over a decade of changes in the tax treatment of charitable donations; while we do not directly consider the effect of tax laws here, virtually all studies find that they do affect giving (see Meer and Priday, 2019, for recent evidence on that question).

The percent of income given is an outcome of particular interest in existing literature and popular media. But regression analysis of this outcome has a serious problem: the dependent and

[13] A handful of studies have examined giving behavior by high-income prospective donors using field experiments, though few consistent conclusions have emerged. See Alston *et al.* (2018); Kessler, Milkman, and Zhang (2019); and Levin, Levitt, and List (2016).

independent variables both contain family income. It is somewhat strange to discuss the impact of income on the percent of income donated while assuming that the denominator of donations over income is held constant.

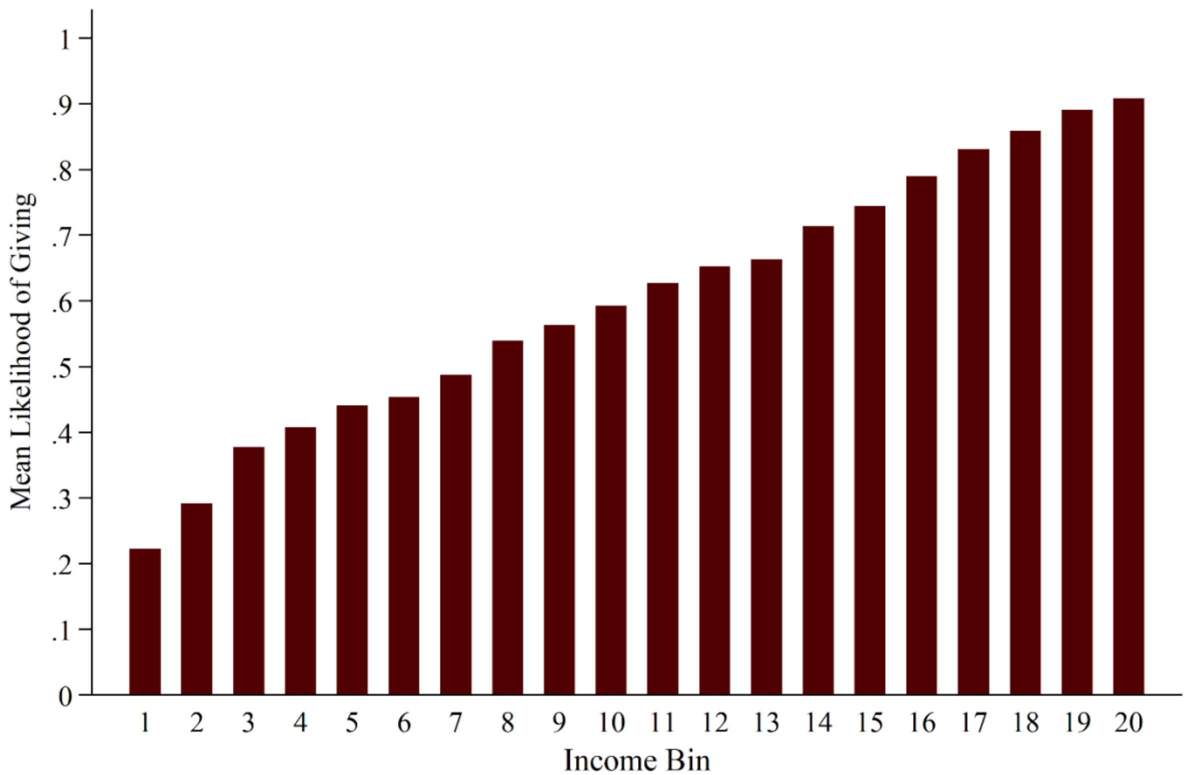
3. Results

3.1 Means and Outliers

We begin by examining mean giving behavior by income (or wealth) bin. This approach does answer the simple question of whether giving by higher-resource households differs from lower-resource households, but without accounting for any characteristics that might be different between those groups that drives philanthropy.

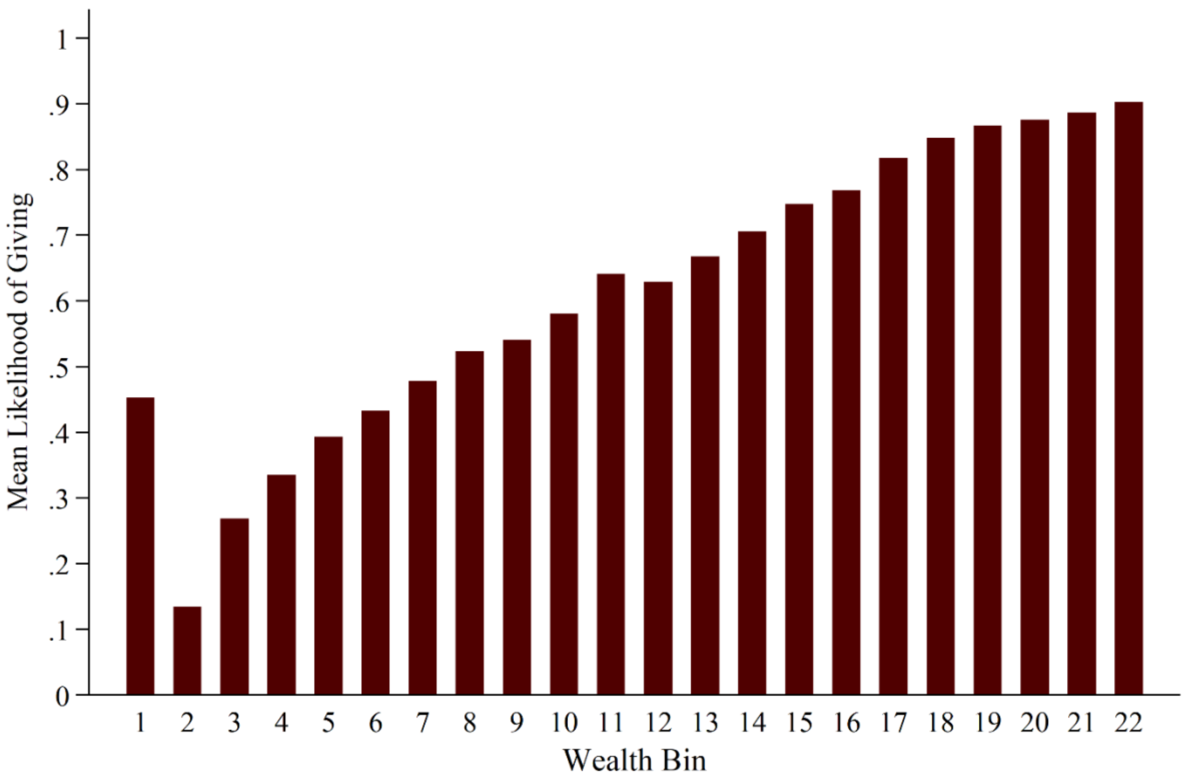
Figure 1 shows the probability of making a donation in a given year across the income distribution. The probability rises monotonically, from 22.3 percent in the lowest bin to 91.0 in the highest. The difference between the likelihood of making any donation between the bottom and 10th bins (37.0 percentage points) is nearly as large as the difference between the 10th bin and the highest one (31.6 percentage points).

Figure 1: Likelihood of Giving, by Income



The relationship for wealth in Figure 2 is slightly more complicated. Recall that the lowest bin is for those with negative wealth, while bin 2 comprises those with zero wealth. The negative-wealth bin has an average likelihood of giving of 45.3 percent, as compared to 13.4 percent for those with zero wealth. It is not until about the 25th percentile of the positive wealth distribution (bin 7) that the likelihood of giving is as high as for those in the bottom bin. This likely reflects the different demographics of those in the bottom bin, who are the youngest group on average, but are as likely to have a college degree or more as those around the 60th percentile of the wealth distribution. Among the ventiles of positive wealth, the likelihood of giving increases steadily from 26.8 percent to 90.3 percent.

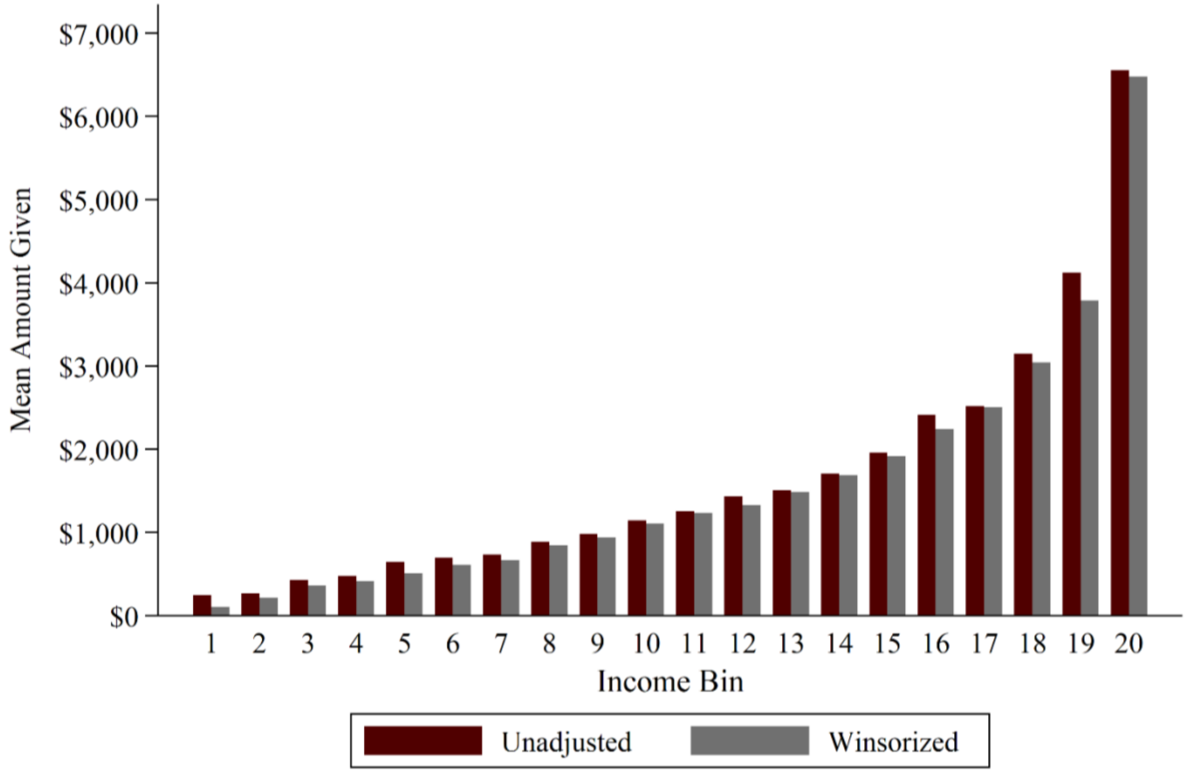
Figure 2: Likelihood of Giving, by Wealth



Notes: Bins 1 and 2 contain households reporting negative and zero wealth, respectively. Bins 3 through 22 are evenly-sized ventiles of positive wealth.

Figures 3 and 4 show the mean amount given by income and wealth bin, both unconditionally and winsorizing at 20 percent of family income. Unsurprisingly, giving increases with higher levels of resources (excepting those with negative wealth). Winsorizing does not change most bins' mean giving very much: the top income bin is reduced to $6,481 from $6,553. The lowest-income bins are affected most in relative terms; the bottom bin's winsorized mean is $108 as compared to $248 unconditionally, while the second bin's mean is reduced to $215 from $271.

Figure 3: Amount Given, by Income



Notes: Both unadjusted and winsorized estimates include households that reported making no charitable donations. Winsorized estimates cap the total amount donated by a household at 20% of family income. See Section 2.1 for a more detailed explanation.

Figure 5, which shows the mean percent of income given by bin, illustrates the sensitivity of results to the presence of outliers. The unconditional mean percent of income by those in the bottom bin is 33.6 percent, including zeroes for the nearly four-fifths of observations in the bin who do not give at all. For the other bins, the mean varies between 1.7 and 2.1 percent. Figure 6 shows percent of giving winsorized at 10, 20, and 30 percent of family income. It is clear that a small number of extreme observations drive the mean for the lowest income bin; indeed, the mean percent given conditional on making a donation is about 146 percent, and 16 observations have giving in excess of 500 percent. Giving as a percent of income tends to be fairly flat across the income distribution when the influence of these outliers is reduced. Table 2 shows that fewer than 6 percent of observations in that bottom bin are affected by winsorizing, but the difference in outcome and interpretation is vast.

Figure 4: Amount Given, by Wealth

Notes: Both unadjusted and winsorized estimates include households that reported making no charitable donations. Winsorized estimates cap the total amount donated by a household at 20% of family income. See Section 2.1 for a more detailed explanation.

Figure 5: Percent of Income Given, by Income

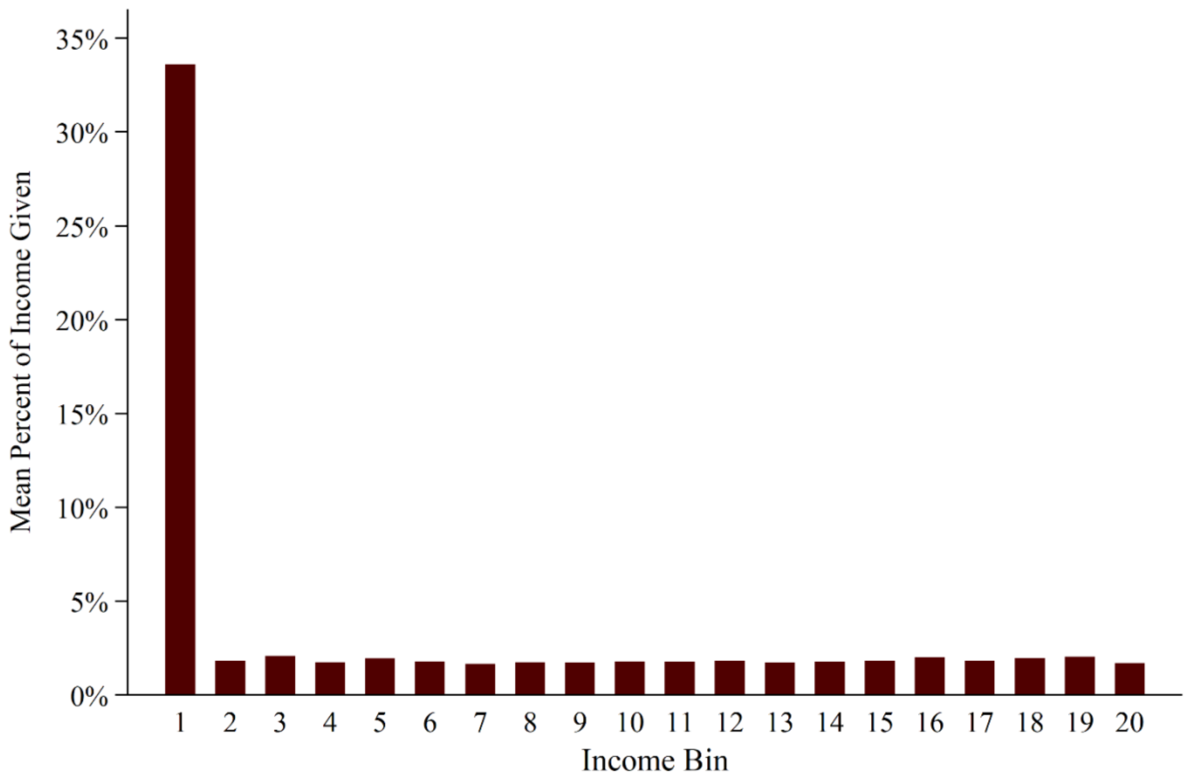
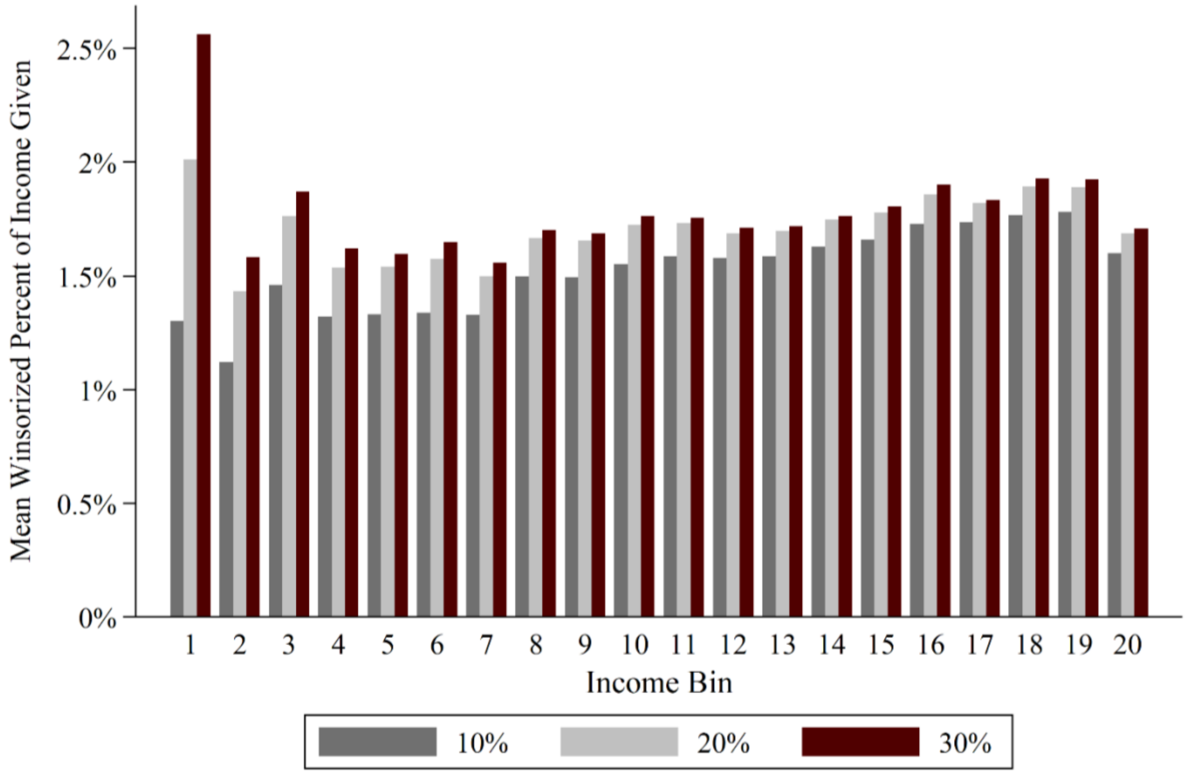


Figure 7 illustrates the mean percent of income given by wealth bin. Once again, the influence of extreme outliers is visible: mean giving at the 25th percentile of the wealth distribution is 18 percent of income, far higher than any other bin, and driven primarily by a single observation (from the lowest income bin). Figure 8 shows the winsorized percent of income given by wealth bin. Excluding the negative-wealth bottom bin, the relationship is strongly positive, rising monotonically from 0.3 percent of income to 3.5 percent of income in the top wealth bin.

Figure 6: Percent of Income Given, Winsorized, by Income



Notes: This figure reports, across income bins, the mean percent of income given winsorized at three levels: 10%, 20%, and 30%. For each of the three levels, the percent of income given by households is capped at that percentage.

As discussed in Section 2.3, one of the primary limitations of the PSID is the lack of data on very high-income households, who make up the bulk of the dollars given. Table 4 shows the mean percent of giving for those groups, based on the Internal Revenue Service Statistics of Income in 2016, which report itemized giving. For simplicity (and as a conservative approach), we assume non-itemizers do not donate: in reality, non-itemizers are likely to donate some positive amount, which makes our estimates a lower bound. While the results are not directly comparable to those from the PSID, the relationship between income and the percent of income given remains strongly positive. We do include this calculation for the \$200,000-\$500,000 bin of adjusted gross income, which corresponds roughly to most observations in our top income bin; mean giving for that group is 1.97 percent, not dissimilar to the 1.72 percent we find in the PSID. The likelihood of giving for these groups (as defined by itemized giving) is between 86 and 94 percent. Higher income bins have higher averages, increasing to 8.6 percent for those with AGIs above $10 million.

Table 4: Higher-Income Giving

IRS SOI Income Groups	Pr (Giving>0)	Mean Amount Given	Mean Percent of Income Given
$200,000 - $500,000	85.2%	$6,302	1.97%
$500,000 - $1,000,000	88.5%	$16,831	2.32%
$1,000,000 - $1,500,000	86.4%	$36,088	2.78%
$1,500,000 - $2,000,000	86.8%	$53,300	2.91%
$2,000,000 - $5,000,000	88.3%	$108,119	3.44%
$5,000,000 - $10,000,000	92.2%	$308,269	4.32%
$10,000,000+	94.6%	$2,661,195	8.57%

Notes: IRS Statistics of Income (SOI) tables report the number of filers in each income group as well as the number of itemizers. Means in this table are calculated assuming that non-itemizers do not make any donations.

Figure 7: Percent of Income Given, by Wealth

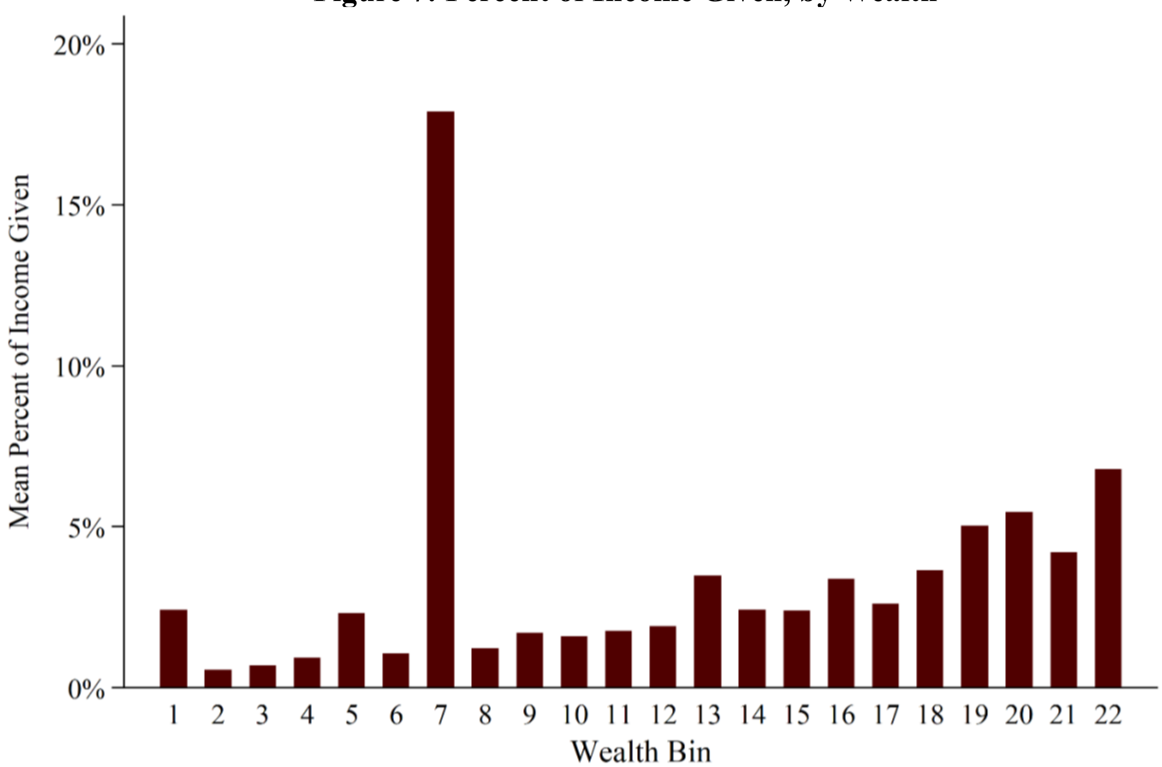


Figure 8: Percent of Income Given, Winsorized, by Wealth

Notes: This figure reports, across wealth bins, the mean percent of income given winsorized at three levels: 10%, 20%, and 30%. For each of the three levels, the percent of income given by households is capped at that percentage.

Taken together, these results show the importance of accounting for outliers in this type of analysis, as well as the need to account for both income and wealth when considering the giving gradient. As noted above, however, these findings document only a strong positive correlation between resources and giving behavior. In the next section, we conduct regression analysis to examine the degree to which income and wealth affect giving, even after taking into account observable individual characteristics that may be correlated with giving.

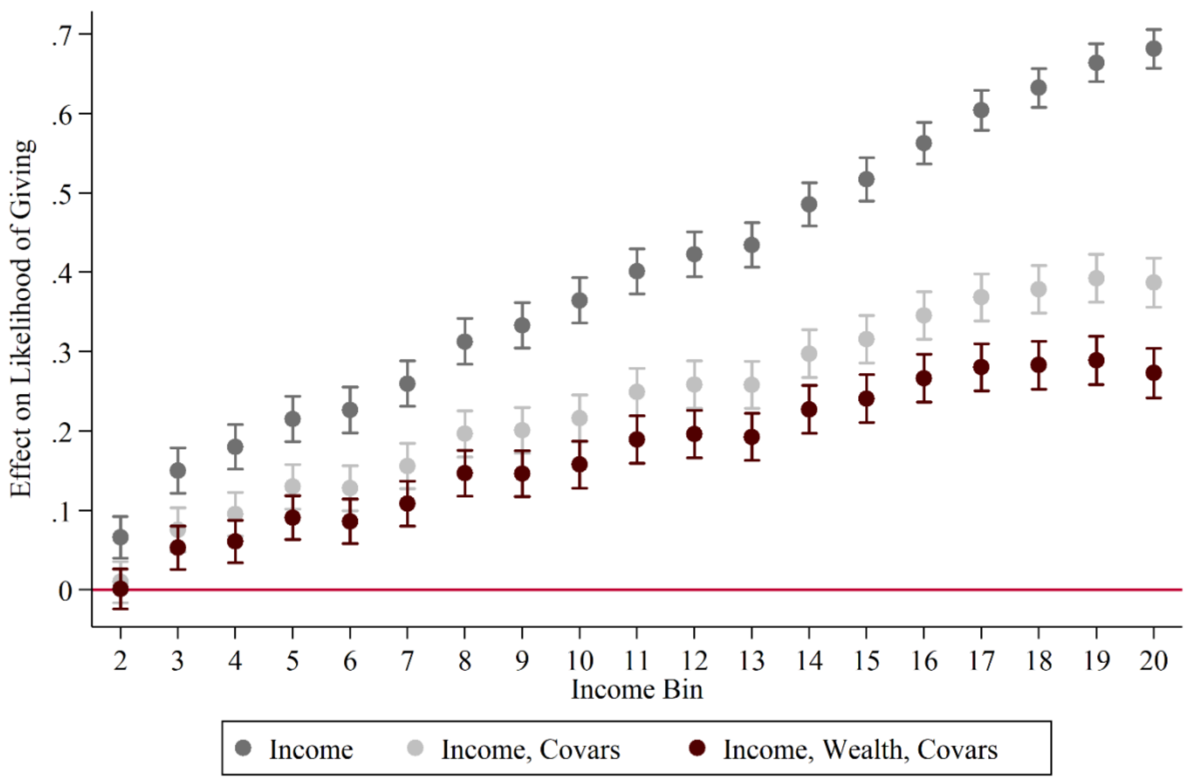
3.2 Ordinary Least Squares Estimates

We examine the degree to which observable characteristics explain the income- and wealth-giving gradients beginning with Figure 9. Each graph includes three sets of coefficients. The first reports the marginal effect of being in an income (wealth) bin with no controls other than indicators for year, relative to the lowest income (wealth) bin. The second adds our full set of covariates: age and its quadratic, indicators for level of education, marital status, state of residence, religious denomination, retired and disabled status, indicators for self-reported health status, race, gender, and a housing price index and its quadratic. The third set of results adds wealth (income) to the controls, thus examining how giving behavior varies across the income distribution holding both observable characteristics and wealth (income) constant.

If, for example, the strong positive relationship between income and giving discussed in Section 3.1 is merely a reflection of other characteristics that are correlated with income and giving (such as education or religious affiliation), then the second and third set of results will show a flat gradient. That is, the independent effect of income on giving, conditional on those observables, will be zero.

Figures 9 through 12 indicate that the relationship remains strongly positive, though these controls do account for a good proportion of the impact. In Figure 9, we show results for the likelihood of giving. Only including year effects, the difference between the top and bottom income ventiles is 68.2 percentage points, as expected from the differences in means. Adding observable characteristics maintains the monotonic relationship, but reduces this difference to 38.7 percentage points. That is, the likelihood of giving is much higher for individuals who are observably similar but have higher incomes, on average. Adding a set of indicators for wealth bin further flattens the relationship, though those in the top bin are still more than 27 percentage points more likely to make a donation than those in the bottom. The differences between the very top income bins are particularly reduced, with the propensity to make a donation roughly the same after the 80th percentile of income.

Figure 9: OLS, Likelihood of Giving, by Income



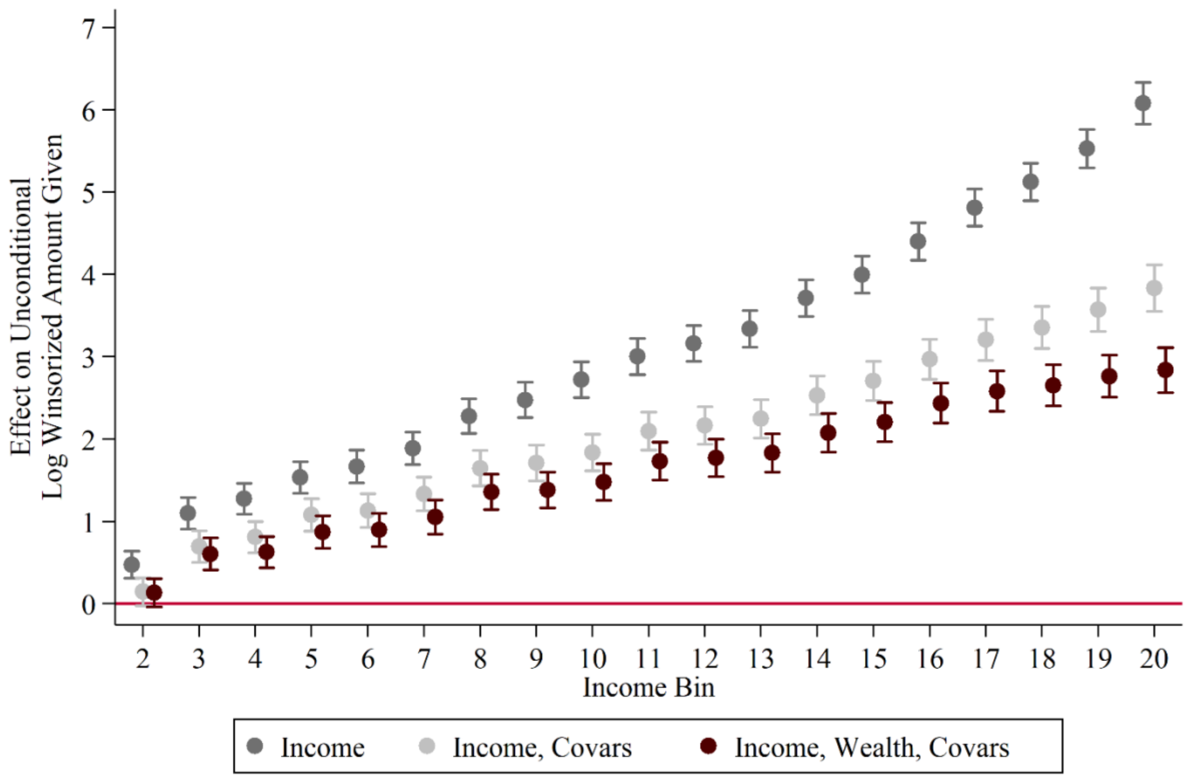
Notes: This figure displays the coefficients for each income bin from OLS regressions. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Covariates include age and its quadratic, indicators for level of education, marital status, state of residence, religion, retired and disabled status, indicators for self-reported health status, race, gender, and a housing price index and its quadratic. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Similarly, Figure 10 shows the relationship between wealth and the likelihood of giving. Interestingly, the higher likelihood of giving by those with negative wealth remains large and significant relative to those with low levels of wealth when including controls (though the difference is reduced by a large margin), suggesting that there is more to this correlation than simply age, education, and other observable characteristics. The top wealth bin is about 15 percentage points more likely to give than those with negative wealth (and 29 percentage points more likely to give than those with zero wealth) when including the full set of controls. Again, the relationship tends to flatten out past the 70th percentile of the positive wealth distribution.

Figure 10: OLS, Likelihood of Giving, by Wealth

Notes: This figure displays the coefficients for each wealth bin from OLS regressions. All specifications include wealth bin and year indicators; the lowest (negative) wealth bin is omitted for comparison. Covariates include age and its quadratic, indicators for level of education, marital status, state of residence, religion, retired and disabled status, indicators for self-reported health status, race, gender, and a housing price index and its quadratic. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figure 11: OLS, Unconditional Winsorized Amount Given, by Income



Notes: This figure displays the coefficients for each income bin from OLS regressions combining the extensive and intensive margins. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Covariates include age and its quadratic, indicators for level of education, marital status, state of residence, religion, retired and disabled status, indicators for self-reported health status, race, gender, and a housing price index and its quadratic. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

In Figures 11 and 12, we turn to effects on the unconditional amount of given, winsorized at 20 percent of family income. As described in Section 2.2, we estimate the extensive and intensive margins separately and then combine them to obtain unconditional estimates. Once again, the income-giving gradient is strongly positive and, in this case, only somewhat attenuated by the inclusion of observable characteristics, including wealth. Those in the top income bin give about 16 times more, on average, than those in the bottom income bin; of course, the mean income in the top bin is 68 times that of the bottom bin. In Figure 12, the wealth-giving gradient is similarly positive, with those in top wealth bin giving about 380 percent more than those with negative wealth, and about 1300 percent more than those with zero wealth.

Figure 12: OLS, Unconditional Winsorized Amount Given, by Wealth

Notes: This figure displays the coefficients for each wealth bin from OLS regressions combining the extensive and intensive margins. All specifications include wealth bin and year indicators; the lowest wealth bin (negative wealth) is omitted for comparison. Covariates include age and its quadratic, indicators for level of education, marital status, state of residence, religion, retired and disabled status, indicators for self-reported health status, race, gender, and a housing price index and its quadratic. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

As discussed above, it is unclear how best to interpret the effects of income on the percent of income given. Nevertheless, for comparison with previous findings, we show these results by income and wealth bin, respectively, in Figures A-1 and A-2, winsorizing at 10, 20, and 30 percent of family income and including wealth and demographic controls. The results do not change meaningfully across these levels of winsorizing, suggesting that it is a small number of extreme outliers that drive the conclusions often seen in the popular press. The percent of income given increases with income, plateauing at about median income, before reducing somewhat for the very top income bin. The results for wealth are clearer: the percent of income given rises monotonically with wealth (excluding those with negative wealth), peaking at about two percentage points higher for the top wealth bin relative to those with negative wealth.

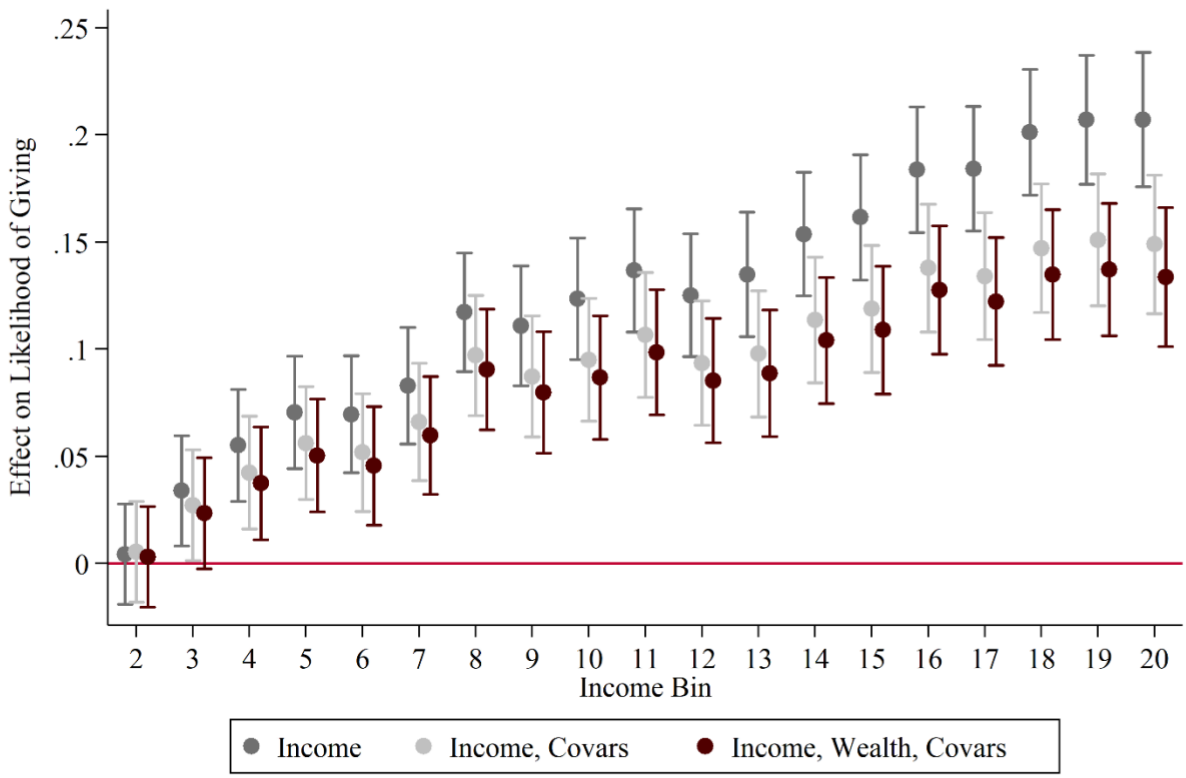
The findings are stark: generosity – as reflected by donations – increases with greater income and wealth. But these results could still reflect unobserved heterogeneity, necessitating stronger controls. We therefore now turn to estimates with individual fixed effects.

3.3 Fixed Effects Estimates

As discussed above, fixed effects estimates account for unobservable, time-invariant attributes, including innate altruism. While these are not necessarily consistent estimates of the underlying marginal propensity to donate out of additional income or wealth, they are closer to that interpretation than the OLS estimates. Suppose, for example, unobserved altruism was correlated with both income and giving but not with the observable characteristics listed in Section 3.2. Then those OLS estimates would still reflect spurious correlation, while estimates including fixed effects would show no relationship between resources and giving.

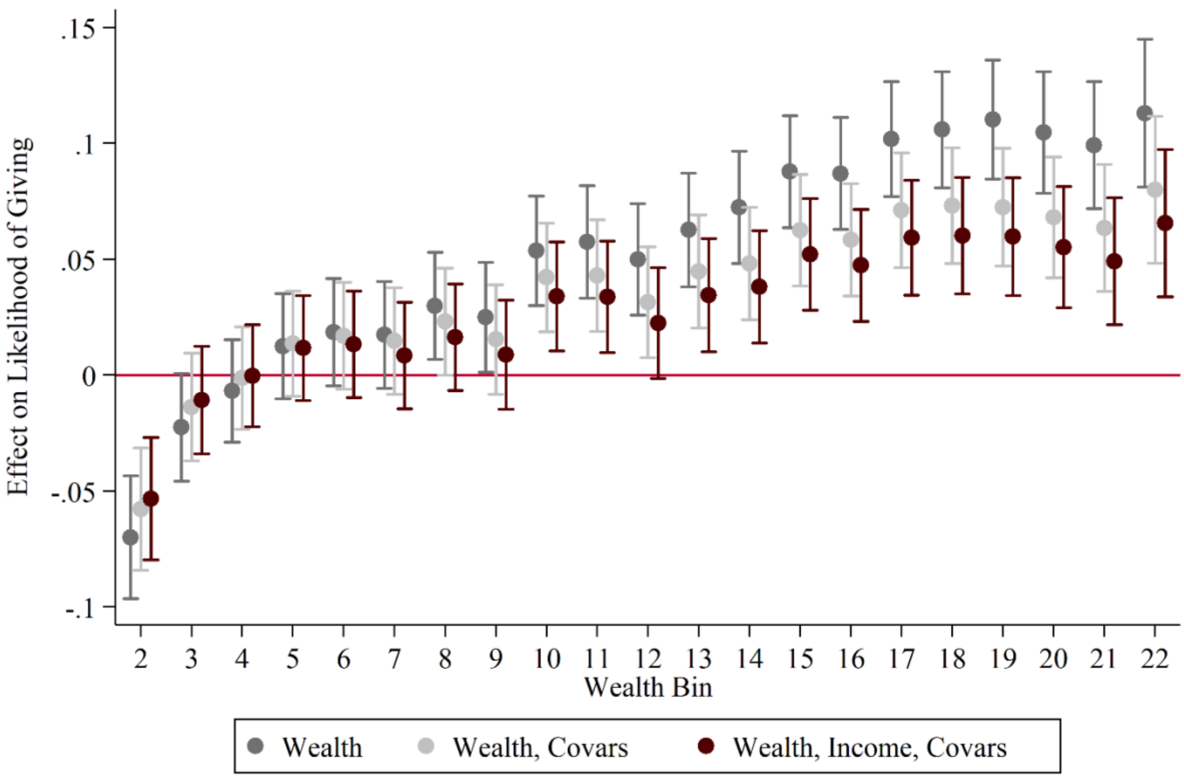
In Figures 13 and 14, we examine the effects of income and wealth on the likelihood of giving. The gradient remains very positive, as with OLS, though the differences between bins are unsurprisingly much smaller. For example, including time-varying covariates and wealth, an individual in the top income bin is 13 percentage points more likely to make a donation than that individual would be had he or she been in the bottom income bin. Note further that the difference between the three specifications is much smaller than with OLS, since the individual fixed effects account for so much of the variation picked up by the covariates in Figure 9. The relationship is similarly positive for wealth. In Figure 14, with those in the top wealth bin are 6.6 percentage points more likely to give than if they had been in the negative wealth bin, and 11.9 percentage points more likely than if they had zero wealth.

Figure 13: Fixed Effects, Likelihood of Giving, by Income



Notes: This figure displays the coefficients for each income bin from fixed effects panel regressions. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Time-invariant covariates from the above OLS regressions are excluded. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figure 14: Fixed Effects, Likelihood of Giving, by Wealth

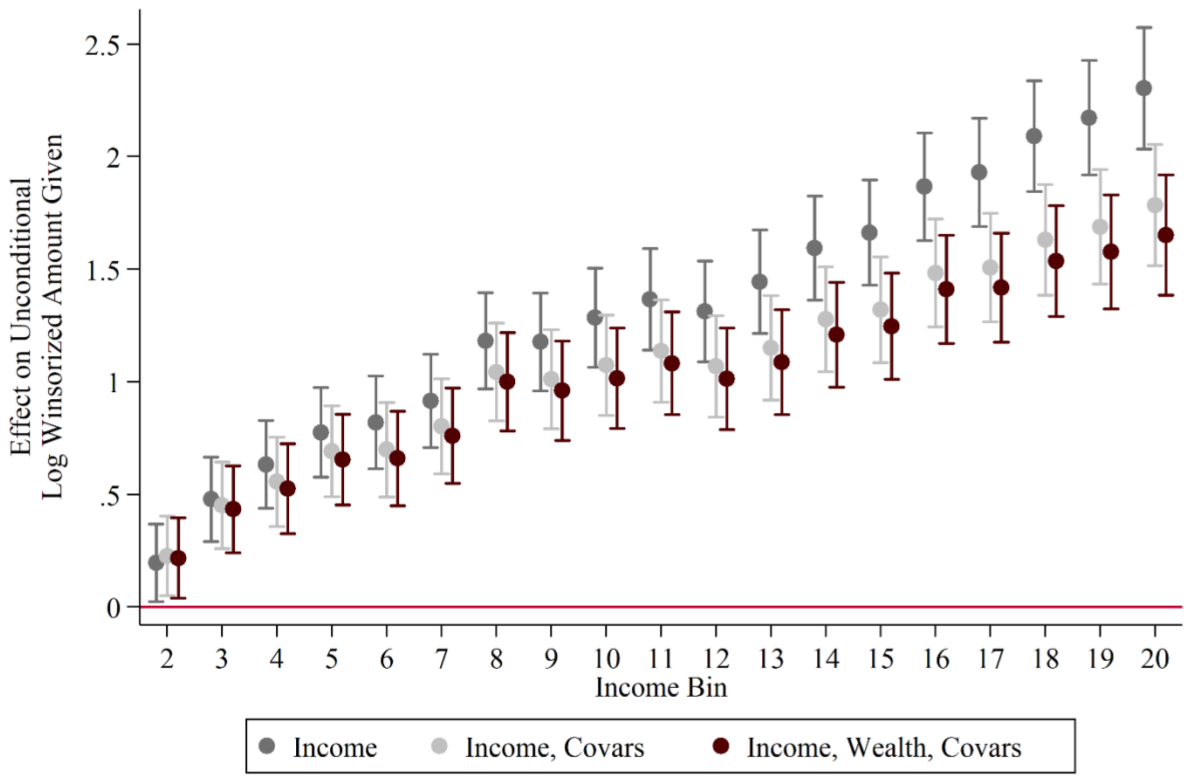


Notes: This figure displays the coefficients for each wealth bin from fixed effects panel regressions. All specifications include wealth bin and year indicators; the lowest wealth bin (negative wealth) is omitted for comparison. Time-invariant covariates from the above OLS regressions are excluded. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figures 15 and 16 examine the effect on the unconditional amount given. Again, the gradient remains strongly positive, with those in the top income bin giving about 420 percent more than they would have had they been in the bottom income bin. And the same holds for higher levels of wealth: those in the top wealth bin give, on average, 100 percent more than they would have had they had negative wealth.[14]

[14] The percent of income results (Figures A-3 and A-4) are difficult to interpret, especially for the effect of income. In contrast to the OLS results and, indeed, those for wealth, the effects of income show a strong negative relationship with magnitudes that cannot be reconciled with the underlying data. We are unable to offer an explanation other than

Figure 15: Fixed Effects, Unconditional Winsorized Amount Given, by Income

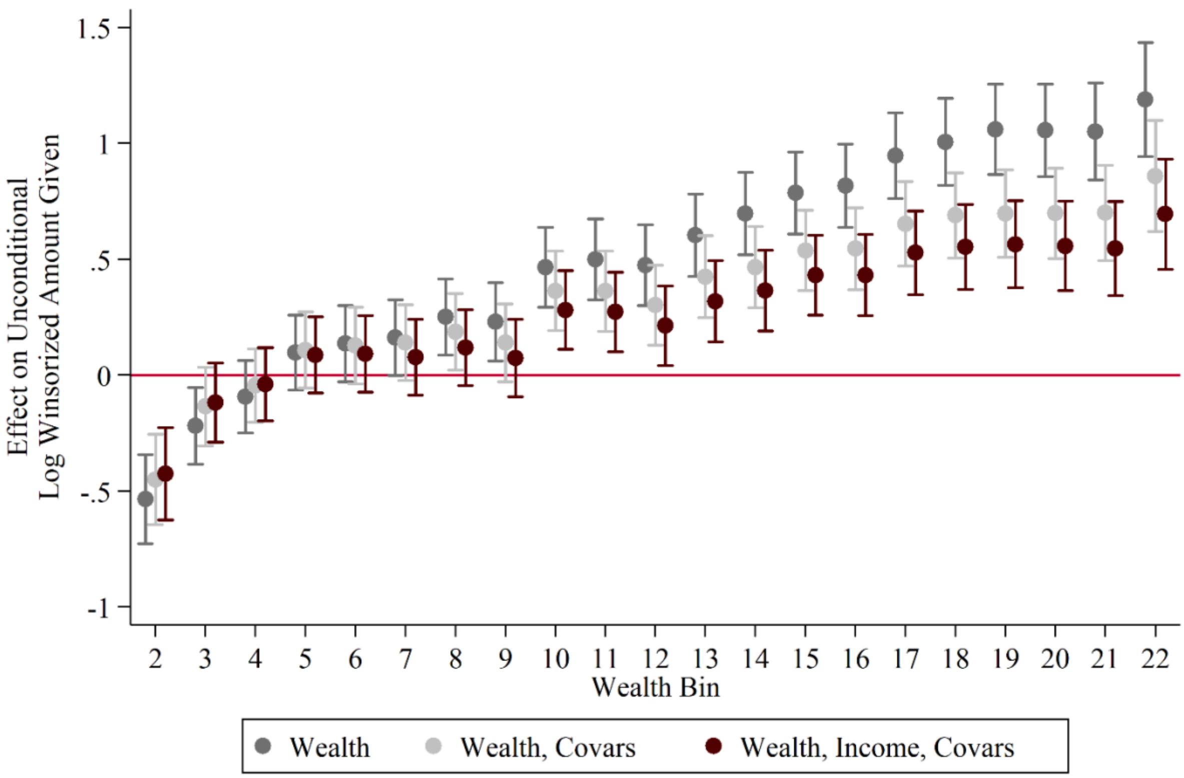


Notes: This figure displays the coefficients for each income bin from fixed effects panel regressions combining the extensive and intensive margins. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Time-invariant covariates from the above OLS regressions are excluded. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

The fixed effects estimates suggest that unobserved heterogeneity is not entirely driving the positive relationship between income (wealth) and donative behavior. By these measures, individuals appear to become more generous as their resources increase, though we caution against making too strong of a causal statement on this front.

that the marginal effect of changing income bins on the percent of income given, estimated within household, is a sufficiently muddled metric that it yields uninterpretable results.

Figure 16: Fixed Effects, Unconditional Winsorized Amount Given, by Wealth



Notes: This figure displays the coefficients for each wealth bin from fixed effects panel regressions combining the extensive and intensive margins. All specifications include wealth bin and year indicators; the lowest wealth bin (negative wealth) is omitted for comparison. Time-invariant covariates from the above OLS regressions are excluded. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

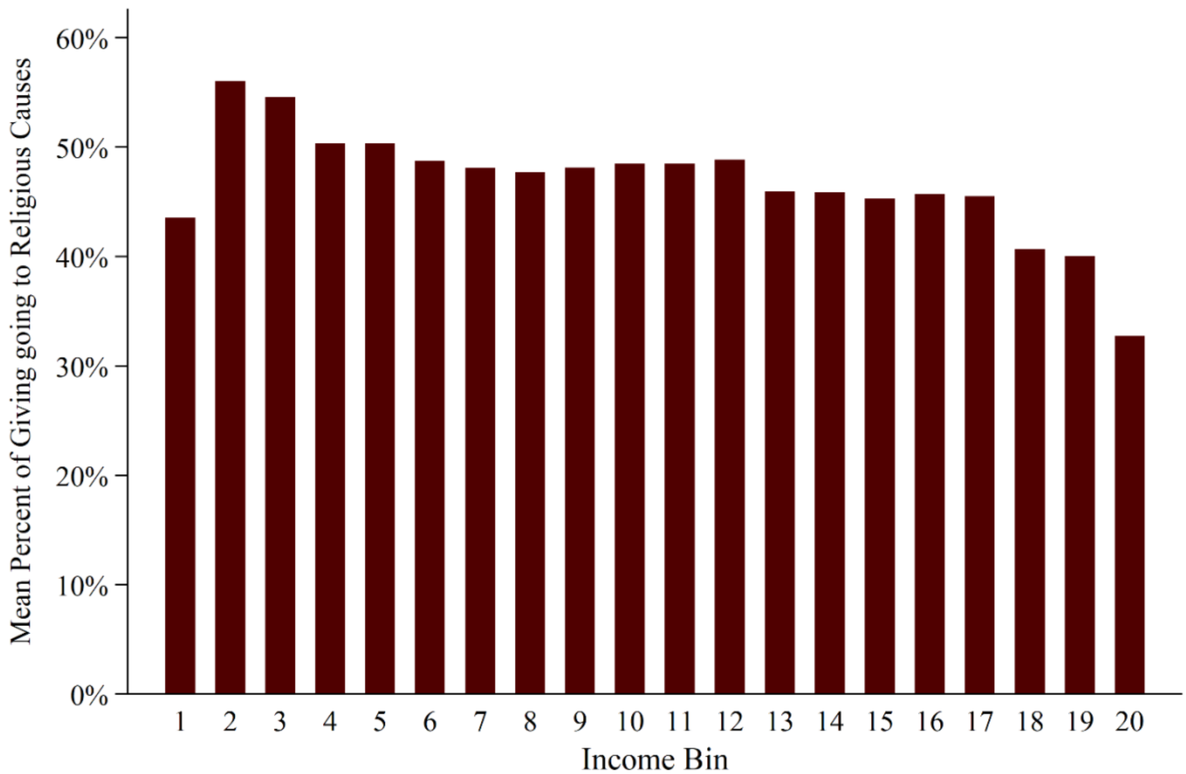
3.4 Religious and Secular Giving

The distribution of giving between religious and secular causes is of independent interest. The popular conception is that giving by lower-income families is tilted towards religious causes, while higher-income families give to the arts and education.[15] The distinction between religious

[15] Iannaccone (1988) provides a theory explaining why the intensity of sectarian religious belief is negatively correlated with income, which naturally implies low-income households will give a larger proportion of their donatable resources to religious groups rather than secular, compared to higher-income groups. Schervish and Havens (1995a) and Jencks (1987) offer this religious commitment as an explanation for why low-income households give larger proportions of their income than middle- and high-income households.

and secular giving is difficult to make at times, but the PSID asks respondents to separate religiously-affiliated charities that work on education or human services issues from religious organizations that provide religious services and the like, designating the former as secular.

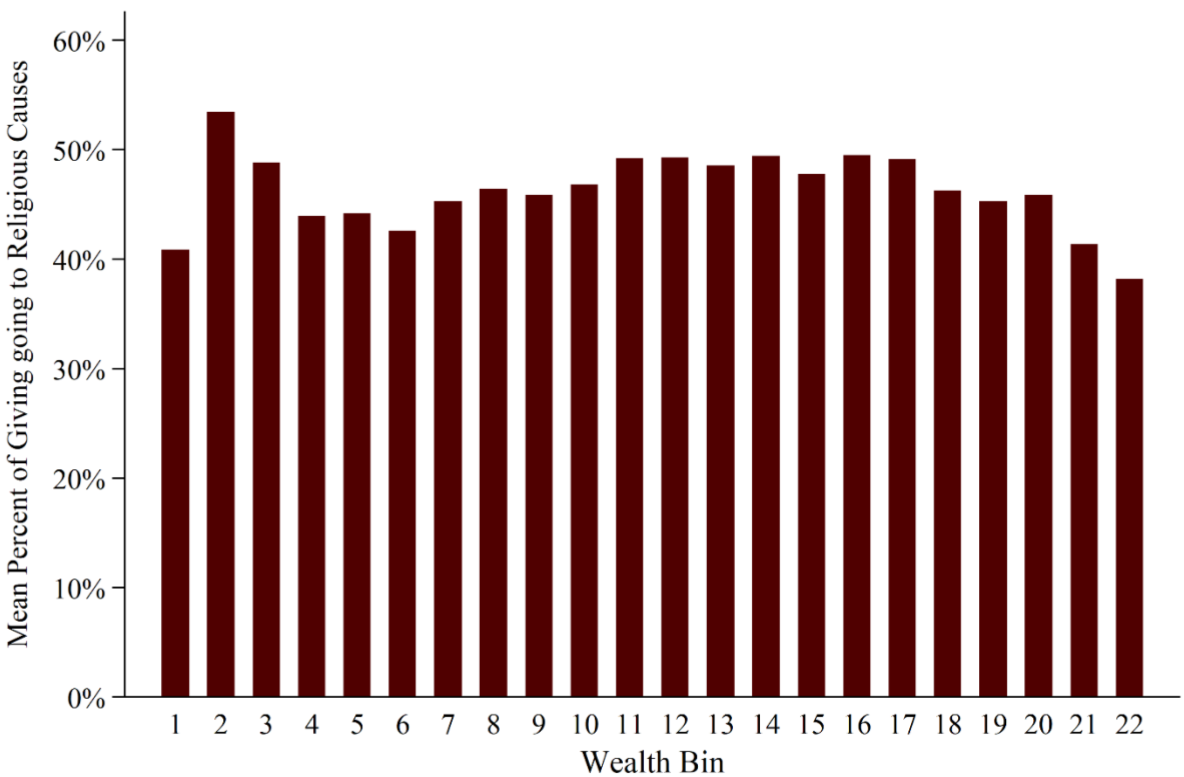
Figure 17: Percent of Giving to Religious Causes, by Income



Notes: Secular giving is aggregated across all charitable causes. Giving to religiously-affiliated or religiously-run charities, such as soup kitchens, hospitals, and schools, are included in secular giving. Religious giving is defined as donations to religious organizations (e.g. churches, mosques). Estimates are calculated by taking mean share of giving to religious causes conditional on making donations within each bin.

In Figures 17 and 18, we examine the mean percent of giving (conditional on making donations) that accrues to religious causes. The share does trend downward over the income distribution, though somewhat surprisingly, the lowest income bin has a smaller share of giving going to religious causes than all but the top few. For the second income bin, about 56 percent of giving is, on average, dedicated to religious causes; for the middle of the distribution, it is about 48 percent, falling to 40 percent and 33 percent for the top two bins, respectively. Only about 25 (30) percent of households that make a gift in the bottom (second) income bin give all of their donations to religious causes. The relationship between wealth and share directed to religious causes in Figure 18 is similar, with a slight decline at the top wealth bins.

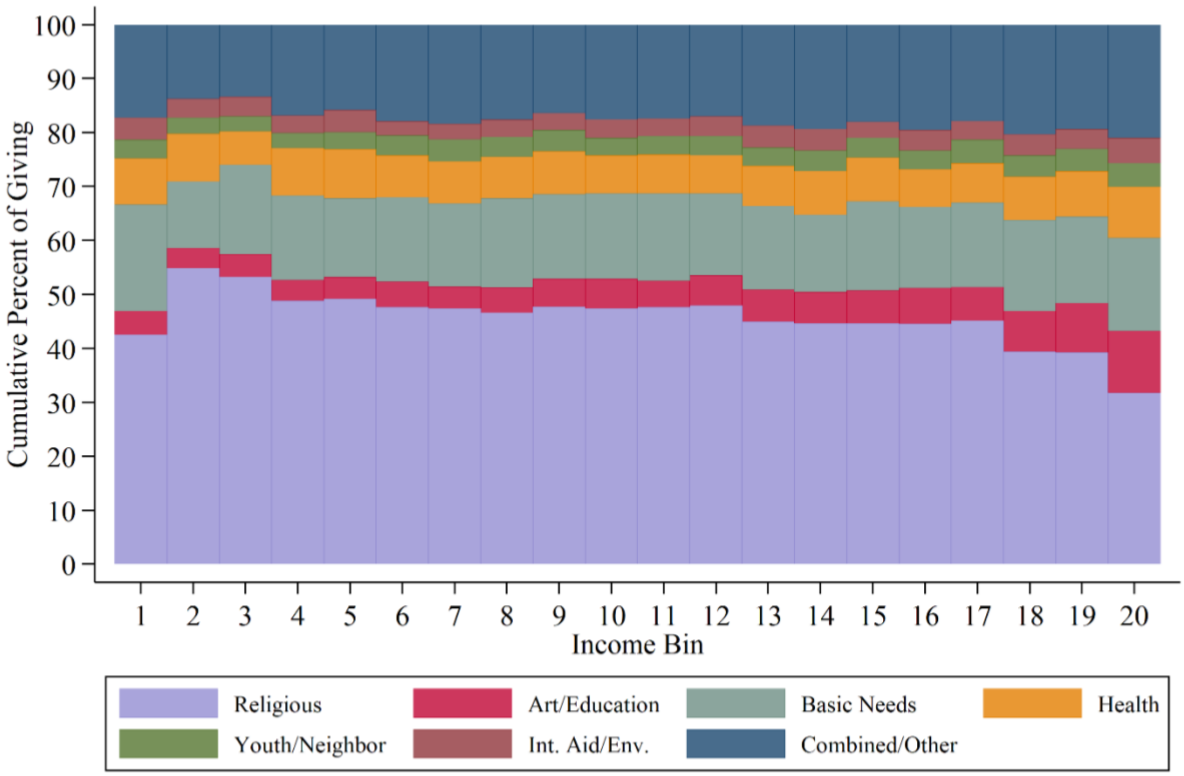
Figure 18: Percent of Giving to Religious Causes, by Wealth



Notes: Secular giving is aggregated across all charitable causes. Giving to religiously-affiliated or religiously-run charities, such as soup kitchens, hospitals, and schools, are included in secular giving. Religious giving is defined as donations to religious organizations (e.g. churches, mosques). Estimates are calculated by taking mean share of giving to religious causes conditional on making donations within each bin.

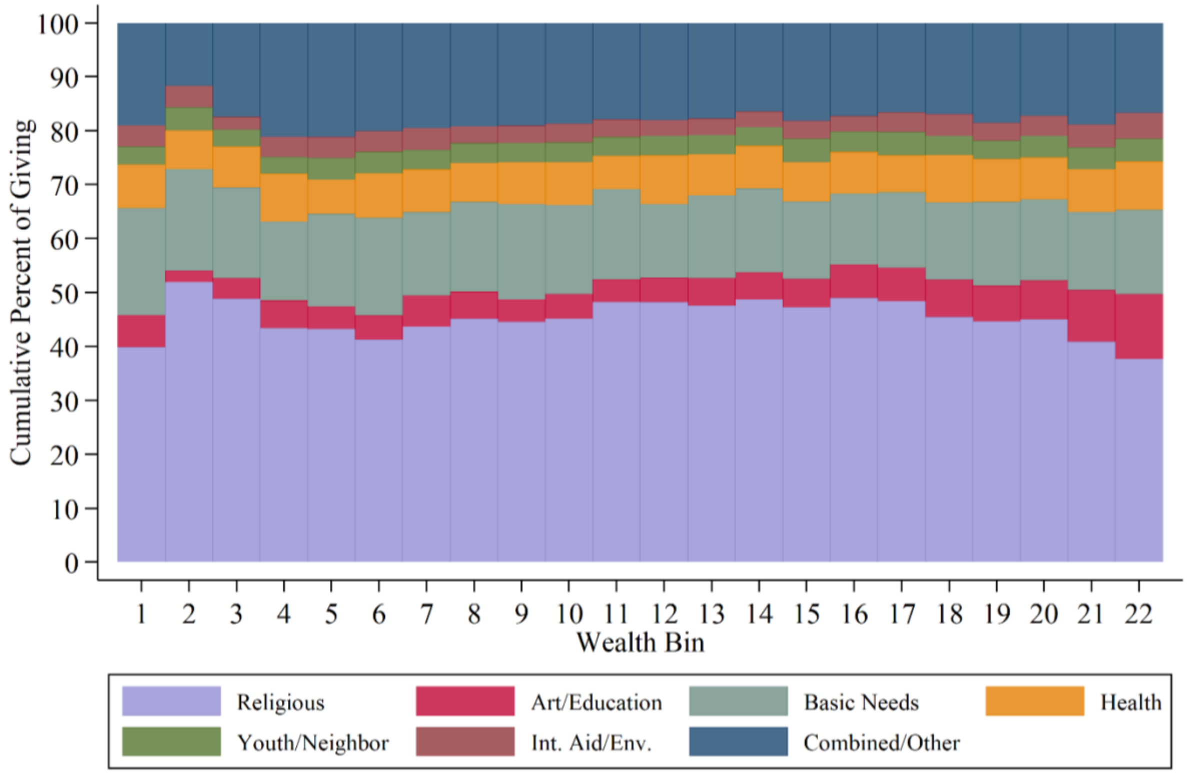
Secular giving in the PSID is divided into ten categories: health, education, art, youth services, community/neighborhood services, basic needs, international (humanitarian) aid, environment, combined purpose organizations, and other. The 2001 wave of the PSID records secular giving in four categories: basic needs, health, education, and combined purpose. We omit data from the 2001 wave from Figures 19 and 20 to preserve comparability.

Figure 19: Percent of Giving to Cause Types, by Income



Notes: Estimates are calculated as mean proportions of total giving to each charity type, conditional on making donations, within each bin. Religious giving is defined as donations to religious organizations (e.g. churches, mosques). The ten categories of secular giving included in the PSID have been grouped as: art and education, basic needs, health, youth and community/neighborhood services, international aid and environment, and combined purpose/other organizations. Estimates exclude PSID year 2001.

Figure 20: Percent of Giving to Cause Types, by Wealth



Notes: Estimates are calculated as mean proportions of total giving to each charity type, conditional on making donations, within each bin. Religious giving is defined as donations to religious organizations (e.g. churches, mosques). The ten categories of secular giving included in the PSID have been grouped as: art and education, basic needs, health, youth and community/neighborhood services, international aid and environment, and combined purpose/other organizations. Estimates exclude PSID year 2001.

In Figures 19 and 20, we break down secular giving into six groups for comparison. Households at the top of income distribution give a larger proportion of their total donations to the arts and education than low- and middle-income households. However, it is untrue that high-income households direct more of their giving to arts and education than to religion. For the top income bin, about 33 percent of giving was to religious organizations while just over 11 percent of giving was to arts- or education-focused nonprofits. For most other causes, giving is proportionally similar across the income distribution. Figure 20 tells a similar story for wealth.

High-wealth households give a larger proportion to art and education compared to lower-wealth households, but they still direct significantly more of their giving towards religious organizations.

4. Conclusions

In this paper, we present systematic evidence on the relationship between income, wealth, and giving. We show that outliers drive the traditional "U-shaped" percent of income given curve. By winsorizing to address these outliers, we show that the percent of income given is actually fairly flat across the income distribution for those making less than $500,000.

We also estimate effects on the extensive and intensive margins of giving in a manner that does not impose restrictions on their relationship, as the Tobit does. In contrast to some of the previous academic research and much of the popular discourse on the topic, we find a strongly positive relationship between resources and giving. We include household-level fixed effects to account for time-invariant, unobserved differences that might bias cross-sectional analyses. We note, however, that our results – even those including fixed effects – cannot necessarily be viewed as the causal impact on giving of additional income or wealth for an individual. Further, the definition of "generosity" that we use is, by necessity, limited, and we take no normative stance on the appropriate interpretation thereof. That said, we believe that our evidence shifts the burden of proof to those who claim that high-income and -wealth individuals are less generous than their less affluent counterparts.

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CHAPTER III

TAX PRICES AND CHARITABLE GIVING:

PROJECTED CHANGES IN DONATIONS UNDER THE 2017 TCJA[16]

1. Introduction

The Tax Cuts and Jobs Act of 2017 (TCJA) made significant changes to the rate structure of the Internal Revenue Code of the United States.[17] One of the many activities potentially affected by this change in marginal tax rates – and, in particular, the near-doubling of the standard deduction – is charitable giving. At the time of its debate and passage, many commentators asserted that charitable giving would be reduced (see, e.g. McQueeney, 2017). Indeed, recently-released aggregate data does indicate a decline of 3.4 percent in giving by individuals in 2018 (GivingUSA, 2019), though drawing a direct causal relationship is difficult because of other changes in economic conditions and incentives to shift giving into the 2017 tax year. Charitable giving is sensitive to macroeconomic conditions (List and Peysakhovich, 2011; Meer, Miller, Wulfsberg, 2017), and this likely impacted giving (Osili and Zarins, 2019).

By reducing marginal tax rates by 1 to 4 percentage points, the TCJA increases the tax price of giving for those who itemize their deductions. For those households, each dollar donated to a

[16] Previously published with J. Meer in *Tax Policy & the Economy*, Vol. 34, pp. 113-138, Robert Moffitt, ed. NBER.
[17] For procedural reasons, the formal title of the bill is "Act to provide for reconciliation pursuant to titles II and V of the concurrent resolution on the budget for fiscal year 2018." We will refer to it by its colloquial name throughout for brevity. Other major provisions in the individual income tax code include the elimination of the personal exemption (and therefore its phase-out), the elimination of the Pease phase-out for itemized deductions, a cap on the deduction for state and local taxes, an increase in the child tax credit, and the use of chained CPI to index provisions of the tax code. The maximum amount of the charitable giving deduction was increased from 50% of Adjusted Gross Income to 60%, which Duquette (2019a) suggests will increase charitable giving by high-income donors substantially. Changes were also made to the estate tax, which may affect charitable bequests (see Bakija, Gale, and Slemrod, 2003; Joulfaian, 1991; and Meer and Rosen, 2013).

qualifying charity reduces their taxable income by one dollar, thus lowering their tax liability by their marginal tax rate. More importantly, though, the increase in the standard deduction means that far fewer households are expected to itemize, thus eliminating the direct tax incentive to make a charitable donation; projections suggest that the proportion of itemizing tax filing units will fall from about 25 percent to about 11 or 12 percent (Gale *et al*., 2018; Joint Committee on Taxation, 2018).

The deduction for charitable giving has existed since the War Revenue Act of 1917, with the justification that charitable organizations may provide valuable societal services while being more responsive than the government. Prior to the TCJA, this provision reduced federal income tax revenue by approximately $57 billion, with about 70 percent of that benefit accruing to households earning over $200,000 per year. Estimates of the reduction in itemized giving suggest that the effects of this provision fell to about $40 billion in 2018 (JCT 2017, 2018). For a discussion of tax policy and charitable giving, see Bakija (2013), Clotfelter (2016), and Duquette (2019b); for a broader look at motivations for philanthropy, see Bekkers and Wiepking (2012) and Gee and Meer (2019).

We provide new estimates of the tax price elasticity of charitable giving using nine waves of the Panel Study of Income Dynamics (PSID), spanning 2001-2017, and apply these estimates to the provisions of the TCJA; we discuss the advantages and disadvantages of these data below. Because of the large number of households that make no donations, we separately estimate the likelihood of giving and the amount given conditional on making a donation using fixed effects models and combine these estimates for an overall effect on donations. Further, since the tax price of giving is endogenous – that is, those who donate large amounts may lower their marginal tax rates, leading to a spurious correlation – we follow much of the existing literature and instrument with the "first-dollar price." That is, we estimate what the household's price of giving would have been without any donations and use that as a proxy for the actual price of giving.

We also examine for the marginal propensity to donate from income (see Meer and Priday, 2019, for more details). The TCJA lowered tax liability for about 80 percent of households, with an average reduction of about $1,600 for all tax units (Gale *et al.*, 2018). The increase in disposable income should increase giving to some degree, offsetting some of the reduction due to an increase in the tax price. Previous academic research on this topic has focused on the direct impact of a change in the tax price of giving, holding all else constant. But a full accounting of the impact of the TCJA on giving should include this change in income.[18]

In line with the previous literature, we find that charitable giving is responsive to tax incentives. A 10 percent increase in the price of giving (equivalent to a reduction in marginal tax rates from, for example, 30 percent to 23 percent) is expected to reduce giving by 10.7 percent, though effects are smaller for those who continue to itemize. We find that the marginal propensity to donate is small and, for most households, the size of the increase in disposable income from the TCJA is sufficiently low that this term does not affect the overall estimates very much.[19] Given that the TCJA is expected to significantly alter itemizing behavior, we estimate our results separately for households that always itemize and those that switch; we find that switchers tend to

[18] There are several thorough and in-depth projections of the TCJA's effect on charitable giving, including Brill and Choe (2018), Gleckman (2018), and IUPUI (2017, 2019). These estimates suggest a reduction of about 4-5% in individual giving. However, these studies draw on an older literature for estimates of the tax price elasticity of giving and do not account for potentially countervailing income effects.

[19] Our fixed effects specification controls for permanent income, and we include controls for wealth, so this might best be viewed as the marginal propensity to donate from transitory income. Further details are in Meer and Priday (2019).

be more sensitive to the tax price. We also find that there are some lagged effects, suggesting that taxpayers take some time to adjust their giving to changes in the tax code.

Of course, our work is subject to limitations. In particular, the PSID does not include many very high earners, who make a large proportion of charitable donations. For example, tax units with earnings over $2 million made $63 billion in deductible contributions in 2016, or about 30 percent of the total, despite making up about 0.1 percent of the population (IRS, 2018). But there are only two such observations in the PSID in that year. We apply our estimates to data from the Internal Revenue Service Statistics of Income to provide some indication of expected effects on these households.

In Section 2, we briefly review the literature on tax incentives for charitable giving. In Section 3, we discuss the PSID and its advantages and disadvantages for this type of analysis, as well as our econometric specification. Section 4 lays out the results, and Section 5 concludes.

2. Previous Literature

The rich literature on the impact of tax policy on charitable giving stretches back over a half-century.[20] Even limiting the focus to papers that use data from the United States, there is huge variety: the use of administrative tax data vs. surveys, panel data vs. cross-sections, approaches to dealing with those who do not make a donation, the inclusion of bequest giving, breakdowns by income level, and the examination of permanent vs. transitory changes in tax prices and income. Peloza and Steel (2005) provide a meta-analysis of sixty-nine papers from this earlier literature and find a weighted average of elasticities of about -1.1 when excluding outliers. More recently,

[20] See, for example, Taussig (1967), Feldstein (1975), Feldstein and Clotfelter (1976), Clotfelter (1980), Reece and Zieschang (1985), Feenberg (1987), Randolph (1995), Auten, Sieg, and Clotfelter (2002), among many others.

Bakija and Heim (2011) use variation in federal and state tax rates on a panel of high-income taxpayers between 1979 and 2006, where nearly all of the observations in the sample have a positive amount of charitable giving. They find that giving is responsive to its tax price, as well as evidence that households adjust to tax changes over time.

Duquette (2016) takes a different approach, examining charities' revenues rather than individuals' donations. He finds significantly larger estimates of the tax price of giving, with an elasticity of about -4 and meaningful differences across types of charities.[21] Backus and Grant (2019), using earlier waves of the PSID, argue that the inclusion of a control for itemizing status is important to account for endogeneity arising from idiosyncratic shocks to giving that change itemization. They concede, though, that if the act of itemizing has its own direct effect on giving, then this term will also reflect a price effect.[22] This potential "itemization effect" is not novel (Boskin and Feldstein, 1977), but has received little attention in the literature, likely because of the difficulty in providing causal estimates. Ottoni-Wilhelm and Hungerman (2007) address it by separately estimating price elasticities for households that always itemize and those that switch between itemizing and not itemizing. We follow their approach, which is particularly valuable in analyzing the TCJA and its large impact on the likelihood of itemizing. They find that "switchers" are much more price-elastic than always-itemizers.[23] In later work, Hungerman and Ottoni-

[21] Meer (2014) discusses the effects of the price of giving in different contexts, including the impact of fundraising or administrative costs and matches, and compares these estimates to the tax price elasticity of giving. Hungerman and Ottoni-Wilhelm (2016) directly compare tax- and match-elasticities for a state-level tax incentive for giving to higher education.

[22] The inclusion of this term changes our estimated elasticity from -1.07 to -0.66, but interpretation of this estimate is unclear given the potential "itemization effect."

[23] They also disaggregate giving into religious and secular causes, though the differences in price elasticities are not necessarily significant. Brooks (2007) finds that the price elasticity of giving differs across causes.

Wilhelm (2016) use a state-level tax credit for donations to educational institutions and find a lower elasticity than the rest of the literature, with estimates around -0.2.

Recent evidence from other countries also suggests that charitable contributions are sensitive to their tax treatment. Adena (2014) and Bönke and Werdt (2015) find that higher-income households in Germany have relatively high tax-price elasticities. Almunia, Lockwood, and Scharf (2018) find elasticities of about -0.35 in the United Kingdom, while Fack and Landais (2010) find elasticities of -0.2 to -0.6 from France's generous tax subsidies.

A frequently-discussed issue in the literature is that short-run responses to tax incentives may be larger than long-run responses because individuals may change the timing of their giving to take advantage of changes in the law (Randolph, 1995; Auten, Sieg, Clotfelter, 2002; Bakija and Heim, 2011). Ottoni-Wilhelm and Hungerman (2007) argue that policymaking in recent years, with tax bills going into effect on short notice and sometimes retroactively, make it difficult for households to anticipate future tax rates. But as discussed in Section 3.3, this issue may be a particular concern with the response to the TCJA.

3. Data and Specification

3.1 Data

The Panel Study of Income Dynamics (PSID) is a biennial household survey that collects information from the previous year on wealth, income sources, and a rich set of household characteristics. The Center on Philanthropy Panel Study (COPPS) data is a PSID module that includes charitable activity to religious and ten types of secular charities. We aggregate household giving to all charities for our primary analysis.

The PSID is especially advantageous for analyzing charitable activity. Wilhelm (2006) shows that the data are superior to other surveys, and compare well to tax return data below relatively high levels of income. While tax return data have the advantage of being more precise and covering high earners, donations only appear in tax data if the household itemizes. This excludes over two-thirds of tax filing units and results in a sample selected for higher income levels. This selection precludes estimating tax price elasticities of giving for households who itemize in some years but not in others. Unlike the PSID, tax return data do not disaggregate giving by charity type. Further, data on wealth are not available on tax returns, which is an important determinant of donative behavior (Bakija and Heim, 2011; James and Sharpe, 2007).[24]

We use nine waves of the PSID spanning 2001-2017. These represent every other calendar year from 2000-2016. The raw sample has 16,146 households with 76,784 household-year observations. We remove 166 observations with negative net-of-tax income. We also remove the low income Survey of Economic Opportunity (SEO) oversample and the 2017 Immigrant Refresher.[25] Consistent with prior literature on tax price elasticities, we omit households that are "endogenous itemizers" – those who would not itemize if they had zero charitable contributions (Clotfelter, 1980; Backus and Grant, 2019; Ottoni-Wilhelm and Hungerman, 2007). These households are more likely to be making the decisions of whether to itemize and how much to donate simultaneously; their inclusion in the estimation makes elasticities appear larger in magnitude than they are in reality. There are 1,776 endogenous itemizer observations. To avoid

[24] Duquette (2018) and Splinter (2019) discuss the impact of inequality on donations by high-income donors.

[25] The 2017 Immigrant Refresher was intended to update the PSID sample to be more representative of the US demographic composition, but only appears for one year in our data. The SEO oversamples low income households which disproportionately lowers the average income of our sample. Combined, omitting them from our sample removes 23,651 observations. Including the oversample and refresher do not change the total elasticity estimate by a meaningful amount.

introducing more measurement error from selectively eliminating observations, we remove all observations for a household that ever endogenously itemized (7,026 observations or 951 households).[26] This leaves us with a final sample of 45,941 observations for 9,711 households. Across all household-years, 56% of households make a donation. Conditional on making a donation, the average (median) gift is $2,045 ($750). The mean (median) income of our sample is $85,696 ($61,158). Table 1 shows summary statistics of the data.

High-income households constitute a large portion of annual donations but are not sampled in large numbers in the PSID. To make predictions about changes in giving for these households, we use summary information on tax returns from the IRS Statistics of Income (SOI).[27] These tables provide estimates of the number of filers, totals from various income sources, and itemized deductions stated in individual income tax returns. Donations are only observed in tax data if the filer itemizes deductions, which most high earners do. We use these tables to generate a "representative tax filing unit" within four bins of adjusted gross income: $500k - $1M, $1M - $5M, $5M - $10M, and $10M+.

[26] We also estimate our specifications including these observations. Counterintuitively, we find that giving is less responsive with respect to the tax respect including this sample, with an elasticity of -0.79.
[27] Specifically, we use the Individual Statistical Tables by Size of Adjusted Gross Income, Table 1.4 and 2.1.

Table 1: Summary Statistics

	Mean	Median	Min	Max
Likelihood of giving	55.59%		0	1
Amount given	$1,135	$117	$0	$722,505
Amount given, conditional	$2,045	$750	$1	$722,505
(Winsorized at 99th percentile)	$1,843	$750	$1	$18,530
Calculated itemization status	24.60%		0	1
Tax price	0.9373	1	0.4763	1.0465
Zero-dollar tax price	0.9371	1	0.4763	1.0465
Family Income	$85,696	$61,158	$0	$7,391,005
Net-of-Tax Income	$74,348	$56,742	$0	$4,819,667
Wealth	$287,982	$53,366	-$2,436,000	$117,649,300
Age	45.82	43	16	104
Retired	0.1432		0	1
Disabled	0.0396		0	1
Married	0.5166		0	1
Health of HOH				
Excellent	0.1958		0	1
Very good	0.3458		0	1
Good to Poor	0.4584		0	1
Number of children	0.759	0	0	11
Catholic	0.2417		0	1
Protestant	0.5031		0	1
Jewish	0.0243		0	1
Other	0.0266		0	1
Atheist/Agnostic	0.1668		0	1
Housing price index	$340,683	$301,900	$148,460	$807,040

Note: PSID samples in every odd year between 2001 and 2017 are included, corresponding to the previous calendar year. The Survey of Economic Opportunity (SEO) oversample and 2016 Immigrant Supplement are removed from the sample, leaving 45,941 total observations across 9,710 households

We use the National Bureau of Economic Research's TAXSIM program to calculate tax liability for each tax filing year in our sample (Feenberg and Coutts, 1993). TAXSIM uses tax-relevant household characteristics, sources of income, and deductions to calculate state and federal tax rates and liabilities. We use these tax liabilities to construct the tax price of giving for household *i* in year *t*. In the literature, this is typically addressed by calculating the price as $1 - I_{it}\tau_{it}$, where I_{it} is a binary variable equal to one if household *i* itemizes in year *t* and τ_{it} is the marginal tax rate. Calculating τ_{it} is not always straightforward, however, because of phase-ins and phase-outs of various credits and deductions, state treatments of charitable contributions, interactions with state taxes, and other vagaries of the tax code.[28] TAXSIM accounts for all these components simultaneously when estimating tax liability. We therefore estimate the tax price of giving as:

$$P_{it} = 1 + \frac{L'_{it} - L_{it}}{100}$$

where L_{it} is the tax liability for household i in year t and L'_{it} is the tax liability calculated after adding $100 to charitable donations. L'_{it} therefore reflects the estimated tax burden less the marginal tax benefit of donating.[29] Donating more will never increase tax liability, so L'_{it} is always less than L_{it}, which bounds $P_{it} \in [0,1]$.[30]

However, L_{it} is endogenous because households can increase donations enough to move into a lower tax bracket. This, in turn, makes P_{it} endogenous, as noted by Auten, Sieg, and Clotfelter (2002). We address this issue by modifying a standard approach in this literature: by

[28] There are 42 states that allow charitable deductions on state tax returns and 6 states that allow federal taxes to be deducted. See Duquette *et al*. (2019) for a discussion of the efficacy of state tax incentives for charitable giving.
[29] We also estimated the models with the more-traditional approach of calculating marginal tax rates to find the tax price of giving. Results were similar, though there were a few unusual marginal tax rates due to notches, kinks, and phase-outs.
[30] The small number of households who are predicted to begin itemizing when $100 is added to their charitable contributions are given a price of 1.

constructing a "zero-dollar" rate where L_{it} is calculated with giving set to zero and L'_{it} with giving set to \$100 for i in t.[31] The corresponding zero-dollar price is used to instrument for the tax price.[32]

The PSID asks respondents whether or not they itemized deductions on their taxes. Ottoni-Wilhelm and Hungerman (2007) note that this itemization status is measured with error, especially for low-income respondents who over-report itemizing. We instead use itemization status calculated by TAXSIM.[33] Though the calculated itemization status likely also introduces some measurement error, we avoid the endogeneity of self-reporting.

We use a similar approach in TAXSIM with high-income bins from the SOI data as with PSID. We observe the percentage of each AGI bin that itemizes its deductions. We use TAXSIM to estimate a single L_{it} and L'_{it} for the itemizers within each bin to find the tax prices because only itemizers have a charitable contributions average listed. For simplicity, we assume that non-itemizers have \$0 of itemizable expenses and a tax price of 1. Section 4.3 discusses in more detail how these estimates are applied.

We use the 2017 wave (2016 tax year) of the PSID to predict changes in giving from the Tax Cuts and Jobs Act (TCJA). The TCJA affected giving primarily through two channels: the standard deduction nearly doubled for all filers, removing the incentive to itemize for large portions of itemizers, and changing marginal tax rates. Consistent with other projections, we see the proportion of itemizers go from 19.9 percent in 2016 to an estimated 7.0 percent under our

[31] See Ottoni-Wilhelm and Hungerman (2007), Auten, Sieg, Clotfelter (2002), Backus and Grant (2019), among others.
[32] About 5 percent of the sample has a zero-dollar tax price that differs from its actual tax price. This is not an uncommon issue in this literature, as discussed by Backus and Grant (2019).
[33] Reported and calculated itemization status agree for 80 percent of observations in our sample. 15 percent report itemizing when we calculate that they shouldn't have and 5 percent report not itemizing when they should have. Benzarti (2019) finds that some taxpayers don't itemize even when it is advantageous, due to high compliance costs.

TCJA counterfactual; the overall rates are lower than those found by others because many itemizers have incomes at levels that are not well-represented in the PSID.

3.2 Specification

We estimate the impact of income and the tax price of giving on the extensive and intensive margins of giving separately, then combine the estimates, using two-stage least squares with household and year fixed effects for each specification. Other controls include bins for the level of household wealth; indicators for marital status, whether the head of the household is retired or disabled, his or her self-reported health status, and religious affiliation; continuous variables for household head's age and its quadratic, number of children, a housing price index and its quadratic; as well as state and year effects.

Previous work using samples of high-income taxpayers had few non-givers (e.g. Bakija and Heim, 2011) and did not have to address the well-known problems with observations censored at zero. Including non-donors in the analysis directly may bias findings towards less elastic estimates. Other work uses the Tobit (e.g. Brooks, 2007), though this model suffers from tractability problems with fixed effects, is likely not appropriate when zeroes arise from corner solutions rather than true data censoring, and constrains the marginal effects on the extensive and intensive margins to be related by a constant. This last issue is particularly problematic when considering the impact of, say, income, which may have very different impacts on the likelihood of making a donation and the amount given. The two-part hurdle model separates the decision of whether to give from how much to give conditional on making a donation.[34] Standard errors are clustered at the household level.

[34] See Huck and Rasul (2011) and Meer (2011) for more discussion on the use of this specification for estimates of charitable giving responses; Wilhelm (2008) compares the Tobit to other specifications for charitable giving

The inclusion of household fixed effects controls for time-invariant factors that are correlated with giving and the tax price. The most important of these may be unobserved altruism. For example, more generous individuals may be more likely to succeed in the workplace, leading to a spurious correlation between donations, income, and tax rates. Changes in altruistic behavior that are correlated with changes in income may still lead to spurious correlation, though, such as if a pay raise coincides with a need to signal generosity to others. Additionally, these fixed effects control, in part, for permanent income. We also include controls for household wealth to further account for permanent income.

Since the amount of charitable giving can affect a household's marginal tax rate, the price of giving is endogenous. As discussed above, we construct an instrument calculating the tax price of giving with donations set equal to zero. This will be correlated with the household's actual price, but variation therein is driven by changes in the tax code, rather than any decision of the household.

3.3 Limitations

Like all of the literature on this empirically-challenging question, our work is subject to a number of limitations.

As mentioned previously, the PSID has very few observations on high-income households, who make the majority of donations. Further, the data are arranged at the household level rather than by tax filing unit. This not only makes direct comparisons to previous work using tax returns difficult, but also introduces measurement error into the calculation of the tax price of giving (Butrica and Burkhauser, 1997). For example, a household in the PSID may include two tax filing

estimation. Recent work by Almunia, Lockwood, and Scharf (2018) emphasizes the importance of estimating tax price effects on the extensive margin of giving.

units (such as a dependent who earns income); the household may be assigned a higher marginal tax rate based on its total income than the tax filing units have on their own.

The TCJA's effects may also take some time to be felt fully. Short-run impacts may be larger or smaller than those in the longer run. Donors may have moved giving into 2017 to take advantage of higher tax prices, leading to overestimates of the law's impact on aggregate giving. On the other hand, it may take some time for taxpayers to change their behavior in response to the new law, as the results detailed below suggest. Further, the TCJA incentivizes households to give less frequently but in larger amounts to reach the itemization threshold; the pattern of giving among donors around these cutoffs may change. The increasing popularity of donor-advised funds may play a role in this kind of timing behavior (Andreoni, 2018). The biennial structure of the PSID makes it more difficult to identify these shifts.

Finally, we are applying estimates from a time period with less radical changes in the tax code than the TCJA, at least in regard to the size of the standard deduction. It is unclear whether our results are fully applicable to the specific parameters of the law. Our findings are best viewed as an approximation rather than a firm prediction.

4. Results

4.1 Tax Price of Giving

We begin by estimating the effect of the tax price of giving on the extensive and intensive margins separately. Table 2 shows these results, which also include the controls described in Section 3.2. Column 1 estimates the effect on the extensive margin, and indicates that a 10 percent increase in the tax price of giving reduces the likelihood of making any donation by 1.3 percentage points, a statistically significant change and about a 3 percent change of the mean giving rate. Column 3 estimates the effect on the intensive margin of giving; a 10 percent increase in the tax price reduces the amount given conditional on giving by 3.4 percent. As discussed above, this estimate should not be interpreted as a reflection of the treatment of a higher tax price, since it also reflects a change in the composition of givers. Combining these effects to find the overall tax price elasticity of giving in Column 5, we find that a 10 percent increase in the tax price reduces giving by 10.7 percent. This elasticity is in line with the vast majority of previous work, and suggests that giving is responsive to its tax treatment.

We also examine how charitable giving responds to increases in income in Table 2, noting that we also control for wealth and individual fixed effects; as such, these results should be interpreted as the impact of additional income for a particular household, holding all else equal. The marginal propensity to donate out of income is fairly low: our estimates suggest that, on average, households will donate about 45 cents from an additional $100 of income.

Table 2: Effects of the Tax Price of Giving

	(1)	(2)	(3)	(4)	(5)
	Extensive Margin		Intensive Margin		
	Pr (Give > 0)	1st Stage	Log Giving	1st Stage	Combined
Log Tax Price	-0.130 ***		-0.338 ***		-1.071 ***
	(0.0250)		(0.0746)		(0.1727)
Net of Tax Income, in thousands	4.19×10^{-07} ***	-1.72×10^{-08} ***	2.45×10^{-06} ***	-2.42×10^{-08} ***	2.07×10^{-06} ***
	(7.49×10^{-08})	(4.70×10^{-09})	(2.53×10^{-07})	(6.96×10^{-09})	(5.20×10^{-07})
(Net of Tax Income, in thousands)^2	-3.50×10^{-13} ***	1.03×10^{-14} ***	-1.58×10^{-12} ***	1.55×10^{-14} ***	-3.13×10^{-12} ***
	(7.17×10^{-14})	(2.65×10^{-15})	(2.56×10^{-13})	(4.10×10^{-15})	(5.17×10^{-13})
(Net of Tax Income, in thousands)^3	5.50×10^{-20} ***	-1.44×10^{-21}***	2.48×10^{-19} ***	-2.30×10^{-21} ***	4.91×10^{-19} ***
	(1.27×10^{-20})	(4.32×10^{-22})	(4.76×10^{-20})	(6.88×10^{-22})	(9.22×10^{-20})
Log Zero-Dollar Tax Price		0.994 ***		0.991 ***	
		(0.000959)		(0.00135)	
Observations	45,583	45,583	25,285	25,285	45,474
Number of Households	9,660	9,660	6,778	6,778	9,644

*** p<0.01, ** p<0.05, * p<0.1. In addition to the variables listed, each specification also includes household fixed effects, bins for the level of wealth, marital status, household head's age and its quadratic, number of children, whether the head is retired or disabled, the head's health status, religious affiliation, as well as state and year effects and a housing price index and its quadratic. Standard errors are clustered at the household level and in parentheses. Column 1 reports the results of a linear probability model for the probability of making a gift, instrumenting for the log of the tax price using the log of the zero-dollar tax price. The first stage is shown in Column 2. Column 3 reports the results for the conditional log amount given, instrumenting for the log of the tax price using the log of the zero-dollar tax price. The first stage is shown in Column 4. Column 5 combines the estimates in Columns 1 and 3 and reports the marginal effects on the unconditional log amount given.

Table 3 reports the impact of the tax price of giving on donations including lead and lag terms. As discussed above, there is concern in the literature about anticipatory effects, as well as the possibility that taxpayers take time to fully adjust to a new tax regime. Column 1 includes a term for the lead of the log of tax price (instrumented with the lead of the log of the zero-dollar tax price). We find little evidence of anticipatory or timing effects; the coefficient is fairly small and imprecisely estimated. This is perhaps unsurprising, given that the PSID's waves are two years apart. Few of the tax changes over the past two decades have had sufficient time between passage and enactment for households to adjust their giving behavior in such a manner (Ottoni-Wilhelm and Hungerman, 2007). Column 2 includes a lag for the log of the tax price (also instrumented). The lag term – again, for two years prior – is statistically significant and about two-thirds the size of the contemporaneous term. This suggests that even two years after a tax change, households are still responsive to the tax price they faced previously; that is, they adjust slowly. Column 3 includes both a lead and a lag term. The leading term remains small and statistically indistinguishable from zero, while the lagged term does not change much in magnitude or precision. Taken together, this suggests that the effects on charitable giving of changes to the tax code like the TCJA will grow over the first few years after implementation.

Accounting for differences in behavior by switchers and always-itemizers is a matter of some contention (Backus and Grant, 2019). We follow Ottoni-Wilhelm and Hungerman (2007) and divide the sample into households who always itemize and households that switch itemizing status over the sample period in Table 4. As discussed in Section 3.3, it is difficult to know how applicable these results are to changes wrought by the TCJA. In our sample, less than 10 percent of households change itemizing status in each year; 21 percent of households ever change itemizing status and 5.1 percent always itemize.

Table 3: Anticipatory and Lagged Effects

	(1) Lead	(2) Lag	(3) Lead and Lag
Log Tax Price	-0.9944*** (0.1846)	-0.8165*** (0.1859)	-0.8042*** (0.2097)
Log Tax Price (year + 2)	-0.0552 (0.1855)		0.176 (0.2049)
Log Tax Price (year – 2)		-0.5568*** (0.1817)	-0.5625 *** (0.1994)
Net of Tax Income, in thousands	3.27×10^{-06} *** (5.46×10^{-07})	-3.84×10^{-06} *** (5.46×10^{-07})	2.84×10^{-06} *** (6.10×10^{-07})
(Net of Tax Income, in thousands)^2	-2.60×10^{-12} *** (5.09×10^{-13})	-2.66×10^{-12} *** (4.66×10^{-13})	-1.95×10^{-12} *** (4.54×10^{-13})
(Net of Tax Income, in thousands)^3	4.09×10^{-19} *** (8.97×10^{-20})	3.99×10^{-19} *** (7.98×10^{-20})	2.88×10^{-19} *** (7.48×10^{-20})
Observations	34,712	34,776	26,636
Number of Households	7,774	7,792	6,333

*** p<0.01, ** p<0.05, * p<0.1. Each column reports the marginal effects on the unconditional log amount given, calculated by estimating the extensive and intensive margins separately. Lead and lag values are instrumented using the lead and lag values of the log of the zero-dollar tax price. Each specification also includes household fixed effects, bins for the level of wealth, marital status, household head's age and its quadratic, number of children, whether the head is retired or disabled, the head's health status, religious affiliation, as well as state and year effects and a housing price index and its quadratic. Standard errors are clustered at the household level.

Table 4: Effects by Itemization Status

	(1) Always-Itemizers	(2) Sometimes-Itemizers
Log Tax Price	-0.7879 (0.665)	-1.242 *** (0.1911)
Net of Tax Income, in thousands	1.25×10^{-06} (8.82×10^{-07})	4.82×10^{-06} *** (8.62×10^{-07})
(Net of Tax Income, in thousands)^2	-1.34×10^{-12} ** (6.16×10^{-13})	-4.10×10^{-12} *** (1.03×10^{-12})
(Net of Tax Income, in thousands)^3	2.56×10^{-19} ** (1.10×10^{-19})	6.53×10^{-19} *** (1.82×10^{-19})
Observations	3,891	16,076
Number of Households	696	2,614

*** p<0.01, ** p<0.05, * p<0.1. Each column reports the marginal effects on the unconditional log amount given, calculated by estimating the extensive and intensive margins separately. The sample in Column 1 is limited to households that itemize in each year, as calculated by TAXSIM. The sample in Column 2 is limited to households that itemize at least once during the sample period, but not in every year, as calculated by TAXSIM. Each specification also includes household fixed effects, bins for the level of wealth, marital status, household head's age and its quadratic, number of children, whether the head is retired or disabled, the head's health status, religious affiliation, as well as state and year effects and a housing price index and its quadratic. Standard errors are clustered at the household level.

But the TCJA is projected to significantly reduce the prevalence of itemizing, especially for the income groups with representation in the PSID. Among units earning between $100,000 and $200,000, the Joint Committee on Taxation estimates that itemizing will fall from 63 percent to 22 percent. Put another way, the composition of switchers and always-itemizers will change. Itemizing is less likely to change for very high income households; average itemized deductions for units earning over $1 million were $465,000 in 2016, far above the new level of the standard deduction (IRS, 2018).[35]

[35] The elimination of the Pease phase-out for itemized giving also increases the overall value of itemized deductions for households with incomes at the top of the distribution, though this does not affect the tax price of giving.

We find that always-itemizers are much less sensitive to the tax price of giving. The estimated tax price elasticity is -0.79 and is not statistically significantly different than zero, as the estimate is quite noisy. The elasticity for switchers, though, is -1.24 and statistically significant. There are a number of possible reasons for this difference. Switchers may be more aware of the impact of itemizing – and therefore the tax price – on their giving. They may be more strategic in the timing of their giving. Further, the changes in their tax prices from year to year are much larger than for always-itemizers.[36] As such, the data cover a broader range of price changes and may reflect a different relationship than that for the always-itemizers.

4.2 Projections for the Tax Cuts and Jobs Act

The TCJA changed both the price of giving (by altering the standard deduction and marginal tax rates) and the amount of money available to donate by changing tax liabilities. To estimate the net predicted changes under the TCJA, we separately estimate the price and income effects on giving for 10 bins of income from the PSID. Projections for higher-income households are discussed in Section 4.3.

We use the 2016 PSID data from the 2017 wave to project tax prices and post-tax income for 2018 by using TAXSIM under TCJA policies rather than those in place in 2016.[37] We follow TAXSIM's predictions of who would itemize in 2016 and 2018 based on relevant deductions; itemizing behavior changes dramatically for households in the PSID sample. For example, Table 5A shows that 46.1 percent of households with AGI between $100,000 and $125,000 are should itemize in 2016, but only 13.4 percent of those same households would itemize under the TCJA.

[36] For example, the TCJA's change in the top tax bracket increases the tax price of giving by 4.3 percent (a marginal tax rate reduction from 39.6 percent to 37 percent), but an individual in that bracket who stops itemizing because of the increase in the standard deduction sees a price increase of 65 percent.
[37] TAXSIM's calculations also include any state tax changes that took place for the 2018 filing year.

Reductions in itemizing are even more dramatic for slightly higher income bins, with the prevalence of itemizing dropping from 81 percent to 26 percent among those earning between $125,000 and $200,000. The mean tax price of giving increases from 0.947 to 0.980 for all observations in 2016 when applying the TCJA's provisions; among itemizers in 2016, the tax price is projected to increase from 0.751 to 0.905.

As discussed above, we estimate separate price elasticities for always-itemizers and switchers, which we apply to the estimates here. We calculate the number of continuing non-itemizers, continuing itemizers, and switchers from 2016 to 2018 and apply a weighted average of the number, mean giving, and mean price change for each type to the appropriate elasticities to generate the average price change for each bin (Table 5B).

Tables 5A and 5B apply these estimates to the changes from the TCJA for selected income bins. In Panel A, Column 1 reports the number of observations per bin (in the 2017 wave of the PSID, corresponding to 2016). Columns 2 and 3 report the mean tax price of giving and the percent of households itemizing, as calculated by TAXSIM, for that year. Columns 4 and 5 are the estimated tax prices and percent of households itemizing based on the provisions of the TCJA, as applied to the PSID data from 2016. Note that the prevalence of itemizing falls dramatically and, as expected, the tax price of giving increases.

Table 5A: Estimated Effects of the Tax Cuts and Jobs Act

		2016 PSID Data		TCJA Counterfactual Applied to 2016 PSID Data	
	(1)	(2)	(3)	(4)	(5)
Federal AGI	N	Mean Tax Price	Percent Itemizing	Mean Tax Price	Percent Itemizing
\$0 - \$20,000	1,663	0.99	0.48%	0.99	0.12%
\$20,000 - \$30,000	417	0.99	3.84%	0.99	1.20%
\$30,000 - \$40,000	459	0.99	7.19%	0.99	2.61%
\$40,000 - \$50,000	418	0.98	11.24%	0.99	3.11%
\$50,000 - \$75,000	765	0.96	16.08%	0.99	5.49%
\$75,000 - \$100,000	514	0.94	25.49%	0.97	9.73%
\$100,000 - \$125,000	596	0.87	46.14%	0.96	13.42%
\$125,000 - \$200,000	241	0.77	80.91%	0.92	26.14%
\$200,000 - \$300,000	178	0.70	91.01%	0.90	33.15%
\$300,000 - \$500,000	55	0.67	87.27%	0.84	49.09%

This table reports projections of the impact of the Tax Cuts and Jobs Act on itemizing status and tax price using the TAXSIM program. Column (1) reports the number of observations in the PSID sample in that income bin.

Table 5B: Projected Effects of the Tax Cuts and Jobs Act

Federal AGI	(1) Mean Δ in Tax Price	(2) Mean Δ in Giving Due to Tax Price	(3) Mean Δ in Post-Tax Income	(4) Mean Δ in Income-Induced Giving	(5) Mean Net Δ in Giving (2) + (4)
$0 - $20,000	0.0002	-$0.18	$9	$0.02	-$0.16
$20,000 - $30,000	0.0037	-$1.74	$196	$0.27	-$1.47
$30,000 - $40,000	0.0060	-$6	$375	$0.68	-$5
$40,000 - $50,000	0.0125	-$10	$568	$1	-$9
$50,000 - $75,000	0.0224	-$34	$838	$2	-$32
$75,000 - $100,000	0.0336	-$34	$1,338	$5	-$29
$100,000 - $125,000	0.0834	-$154	$1,503	$7	-$146
$125,000 - $200,000	0.1506	-$378	$1,807	$13	-$365
$200,000 - $300,000	0.2009	-$615	$2,759	$26	-$589
$300,000 - $500,000	0.1706	-$848	$9,841	$130	-$718

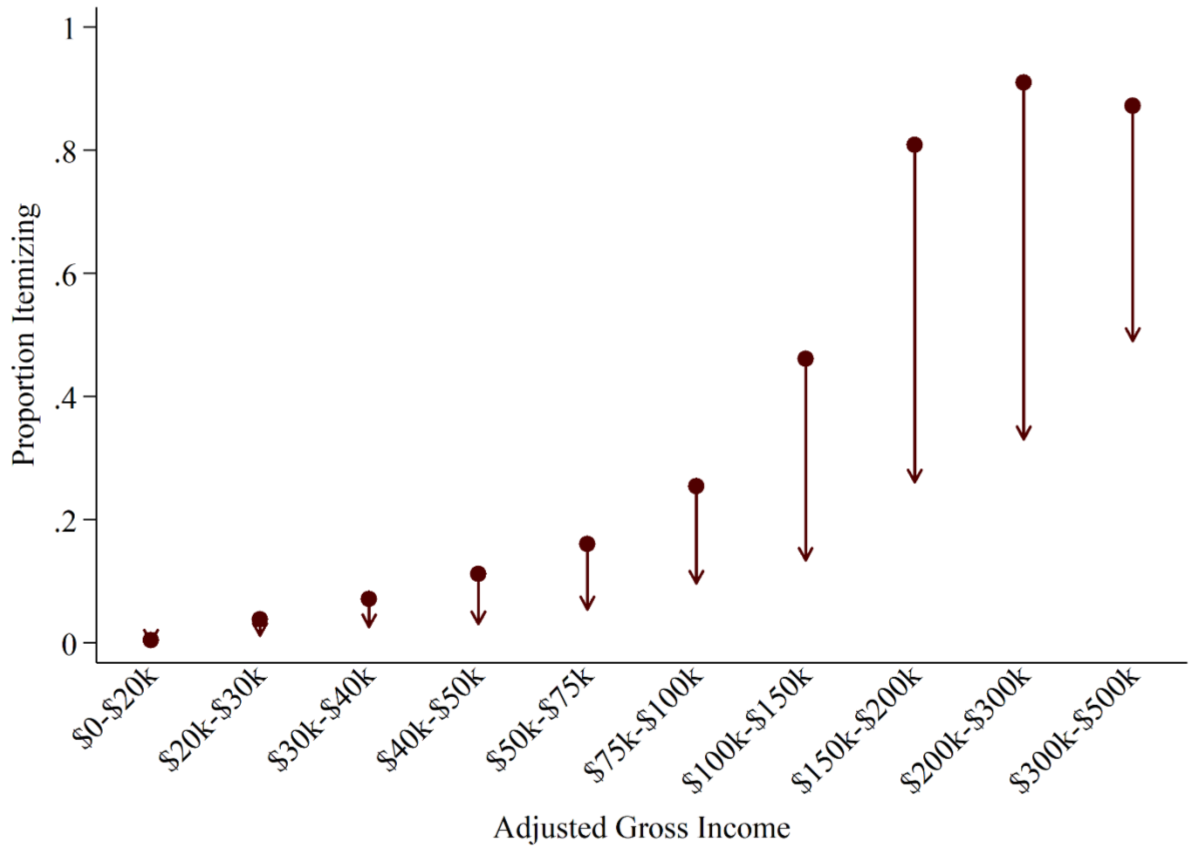
This table reports projections of the impact of the Tax Cuts and Jobs Act, estimating mean changes in the tax price of giving and tax liability using the TAXSIM program. Estimates from Table 4 are applied to calculate the changes in giving due to changes in the tax price, as well as those due to changes in post-tax income.

Table 5B displays the mean change in the tax price of giving in Column 1, and applies our elasticity result to calculate the estimated change in giving induced by the change in the tax price in Column 2.[38] As expected, the changes for lower-income bins are small, since few households itemize in that range. Column 3 shows the average change in income expected from the TCJA, and Column 4 applies the marginal propensity to donate out of income (calculated from Table 4) to those figures. Column 5 combines the estimates. As described above, these income-induced increases in giving are fairly small. For example, for households with AGI between $75,000 and $100,000, the income-induced increase is about 15 percent of the change due to the tax price, and only about 4 percent for households between $100,000 and $300,000. For the highest-income bin in the PSID, though, the income-induced increase in giving offsets about 15 percent of the decrease.

Figure 1 plots the projected changes in itemizing status by income group, while Figure 2 does so for the tax price. Figure 3 shows the projected changes induced by the tax price changes in the TCJA as well as the amount net of income-induced increases in giving. Figure 4 shows actual giving in 2016 by income group against the projection under the TCJA.

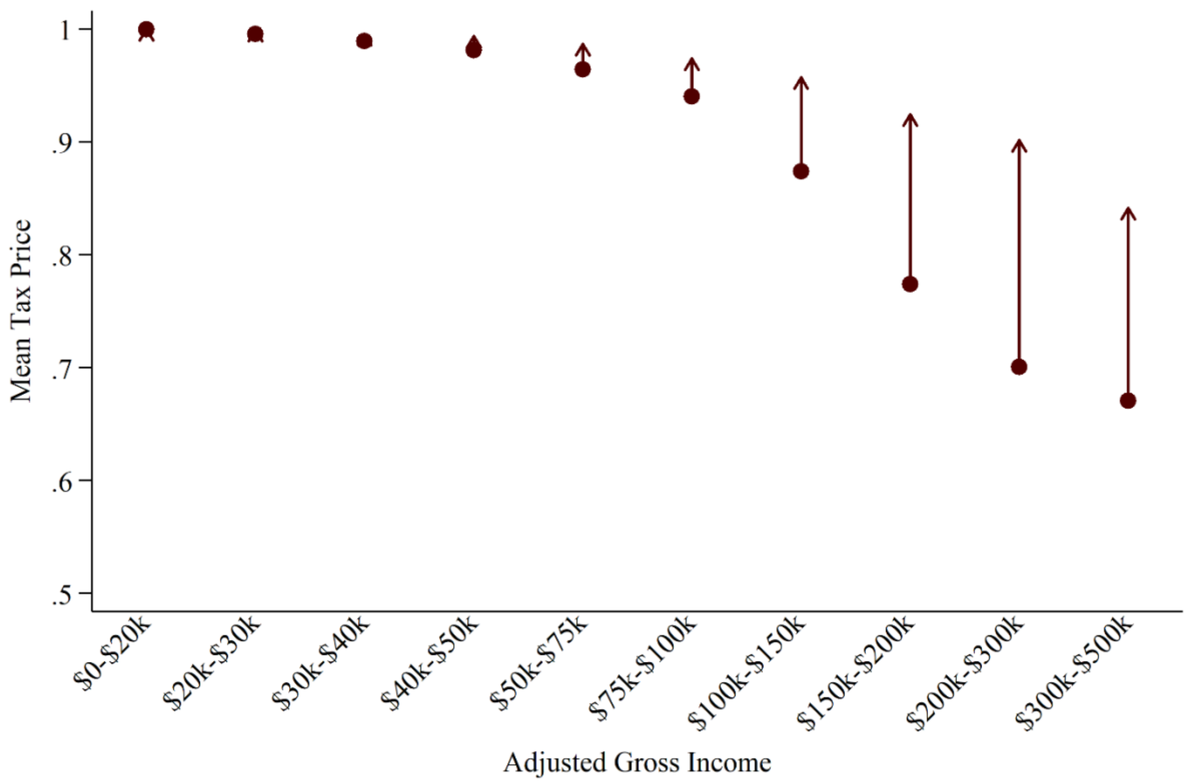
[38] We winsorize giving at the 95th percentile for this calculation; a small number of outliers increases mean giving by an unrealistic and unrepresentative amount.

Figure 1: Changes in Proportion of Households Itemizing in 2016 and Counterfactual Predicted Under Tax Cuts and Jobs Act



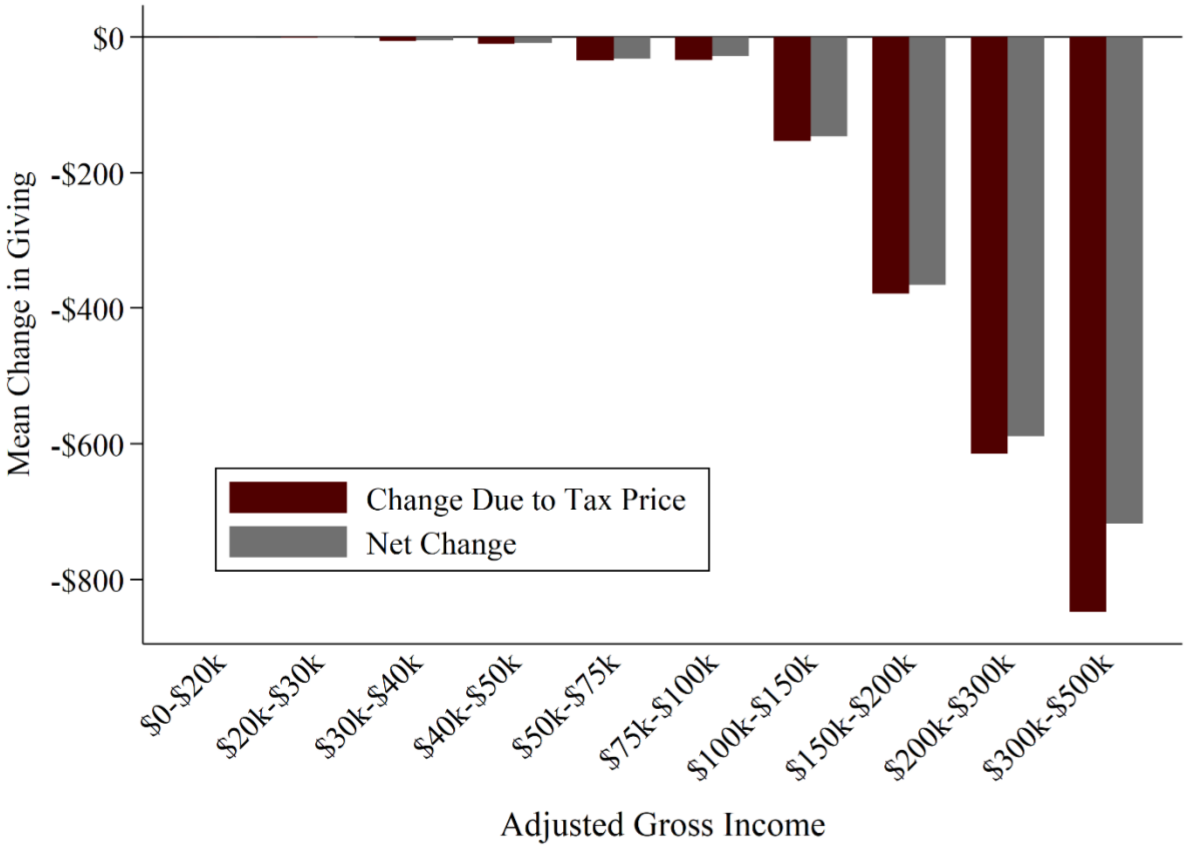
This figure displays the changes in each bin of net-of-tax income in the 2017 wave of the PSID (corresponding to 2016) between the proportion of households itemizing in 2016 and that projected under the TCJA. These results correspond to Columns (3) and (5) of Table 5A.

Figure 2: Changes in Mean Tax Price in 2016 and Counterfactual Predicted Under Tax Cuts and Jobs Act



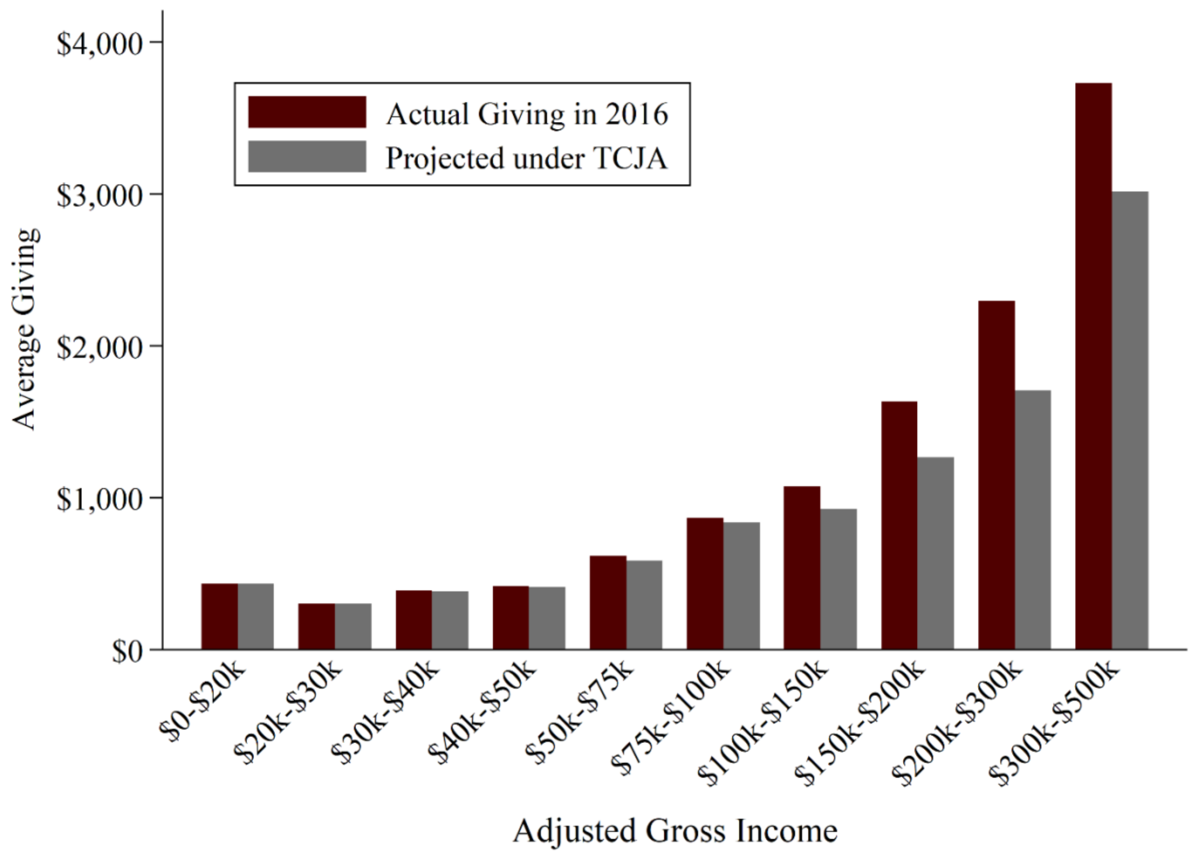
This figure displays the changes in each bin of net-of-tax income in the 2017 wave of the PSID (corresponding to 2016) between the mean tax price of giving for households in 2016 and that projected under the TCJA. These results correspond to Columns (2) and (4) of Table 5A.

Figure 3: Changes Between 2016 Giving and Counterfactual Predicted Under Tax Cuts and Jobs Act



This figure displays the changes in each bin of net-of-tax income in the 2017 wave of the PSID (corresponding to 2016) between actual giving and that projected under the TCJA. The blue bars reflect the projected change solely based on the tax price, corresponding to Column (2) of Table 5B. The red bars includes the change induced by the reduction in tax liability, corresponding to Column (5) of Table 5B.

Figure 4: Differences Between 2016 Giving and Counterfactual Predicted Under Tax Cuts and Jobs Act



This figure displays mean donations in each bin of net-of-tax income in the 2017 wave of the PSID (corresponding to 2016). It also displays the estimated mean giving for that bin based on the TCJA's impact on the tax price of charitable giving and the increase in net-of-tax income. The difference between these two bars corresponds to the results in Figure 4 and in Column (5) of Table 5B.

4.3 Projections for High-Income Tax Filing Units

Unsurprisingly, high-income donors make a large share of total donations. Even a small percentage of a ten-million-dollar income is significantly more than the combined donations of tens of thousands of lower-income households. As such, the behavior of these households in the face of changes to the tax code is of significant interest. Unfortunately, as detailed above, the PSID simply does not sample a sufficient number of these high earners. Nevertheless, we estimate some simple projections to provide insight on expected changes in giving and the degree to which additional disposable income from the TCJA might offset these changes.

We use the Internal Revenue Service Statistics of Income (2018) to create representative tax filing units using the means of the various components of income and itemized deductions for the 2016 tax year. We group them together into bins above $500,000 ($500K-$1M; $1M-$5M; $5M-$10M; $10M+). We assume that households earning above $1 million continue to itemize at the same rate as they did prior to the TCJA, as the means of itemizing exceeds the new standard deduction by a significant amount. Of course, there will be some marginal tax filing units that switch to the standard deduction. That would tend to increase our estimate of the reduction in giving, though we expect the number of switchers to be small, even with the cap on state and local tax deductions. For the $500,000-$1M group, we apply estimates from the Tax Policy Center (2018) for the expected number of units that stop itemizing.

We then estimate the tax price of giving as described above, using TAXSIM, as well as calculating the expected change in tax liability. Our estimates for the latter are similar to those by the Joint Committee on Taxation (2019) and Gale *et al*. (2018).

We can apply our estimates of the tax price elasticity of giving to these calculations, though we must make the assumption that our estimated elasticity are valid for these higher-income bins. Our estimates for the marginal propensity to donate out of income yield implausible predictions that are orders of magnitude larger than a reasonable amount; it is clearly not reasonable to apply estimates from households earning less than $300,000 to households at the upper reaches of the income distribution. We therefore show estimates for a range of plausible values for the marginal propensity to donate in Table 6.

Table 6: Projected Effects of the Tax Cuts and Jobs Act for High Earners

				Mean Net Δ in Giving				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Federal AGI	Mean Δ in Tax Price	Mean Δ in Giving Due to Tax Price	Mean Δ in Post-Tax Income	MPD = 0.01	MPD = 0.02	MPD = 0.03	MPD = 0.04	MPD = 0.05
\$500K - \$1M	-0.029	\$234	\$14,091	\$374	\$515	\$656	\$797	\$938
\$1M - \$5M	0.024	-\$2,054	\$19,965	-\$1,854	-\$1,655	-\$1,455	-\$1,255	-\$1,056
\$5M - \$10M	0.024	-\$10,036	\$44,779	-\$9,588	-\$9,140	-\$8,692	-\$8,245	-\$7,797
\$10M+	0.029	-\$104,838	\$140,663	-\$103,431	-\$102,025	-\$100,618	-\$99,211	-\$97,805

This table reports projected effects of the Tax Cuts and Jobs Act for higher-income bins. Changes in tax price and post-tax income are calculating using TAXSIM on representative tax filing units from the IRS Statistics of Income. Columns (4)-(8) report the overall net change in giving under different assumptions of the marginal propensity to donate (MPD) out of the change in income.

Even with our assumption that they continue itemizing, households earning above $1 million see substantial reductions in charitable giving due to changes in tax price. However, particularly for the highest levels of the income distribution, the reduction in tax liability is sufficiently large that reasonable values for the marginal propensity of giving offset a meaningful portion of the tax-price-induced reduction. For example, a marginal propensity to donate of 0.02 for households with AGI between $1 and $5 million offsets about 20 percent of the reduction.

Finally, we scale our estimates in Sections 4.2 and 4.3 up by the number of tax filing units in each income bin. We estimate that, had they been in effect in 2016, the provisions of the Tax Cuts and Jobs Act would have reduced charitable giving by about $9.8 billion, or about 3.5 percent of total individual giving.

While lacking many of the important determinants of charitable giving, including wealth, new research on the marginal propensity to donate and tax price elasticity of giving of very high-income households using administrative tax data would be valuable.

5. Conclusions

This paper provides updated estimates of the tax price elasticity of charitable giving using the Panel Study of Income Dynamics. We apply these results to the provisions of the Tax Cuts and Jobs Act of 2017 and predict significant reductions in charitable giving, primarily arising from the reduction in the number of households that itemize their deductions.

We note a number of limitations to this study, particularly in regards to the relative dearth of very high income households in the data. Additionally, the TCJA’s changes to the standard deduction are outside the scope of changes to the tax code covered in our data. It is difficult to know how accurate our extrapolations are, particularly for very high income households. But we do show that plausible values for the marginal propensity to donate out of income offset some portion of the tax-price-induced reduction in giving. Projections that do not account for this countervailing effect are likely to overestimate the impact of reductions in marginal tax rates on giving.

We also find evidence that taxpayers take at least several years to fully respond to changes in the tax price of giving. To the extent that charitable giving is habit-forming (Rosen and Sims, 2011; Meer, 2013), and that changes to incentives to give through one form of philanthropy alter giving to others (Gee and Meer, 2019; Scharf, Smith, and Wilhelm, 2017; Brown, Meer, and Williams, 2019), the ripple effects of the law may take years to be felt.

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CHAPTER IV

EFFECTS OF REMOVING RELIGIOUS GROUPS' TAX-EXEMPT STATUS: A PRELIMINARY ANALYSIS

1. Introduction

In an LGBTQ town hall during his 2020 Presidential campaign, Beto O'Rourke said he would revoke the tax-exempt status of churches that oppose same-sex marriage (Cook, 2019). There was considerable backlash from conservatives and Christians but also from economists and popular media writers who noted there would be several negative consequences of such a decision (Strain, 2019; Inazu, 2019). Some dismissed Beto's idea out-of-hand as politically implausible and therefore moot.

This is not a fringe issue or idea, however. The tax-exempt status of religious groups that oppose same-sex marriage came up in oral arguments during *Obergefell v. Hodges* (Bailey, 2015; Oppenheimer, 2015).[39] Religious organizations have historically been the strongest dissenting voice against expanding rights for LGBT people. As support for equal protection under the law for same-sex couples rises (Pew Research Center, 2019) the intersection between religious freedom and civil rights will likely become an even more pressing issue.

Emerging civil rights jurisprudence is not the only motivation for revoking the tax-exempt status of religious organizations. Some writers in popular media outlets claim the tax-exemption for churches is inefficient (Yglesias, 2013), dramatically decreases tax revenue (Matthews, 2013), and does not fulfill the original intent of the law (Fleischer, 2015). The "scholarly" work behind

[39] Obergefell v. Hodges 576 U.S. 644 (2015) was a landmark Supreme Court case that ruled that the right to marry was extended to same-sex couples, effectively legalizing same-sex marriage.

these opinions is highly suspect and there is by no means consensus (Strain, 2019; Elliot, 2017), but clearly some believe there should be a discussion about tax exemption for religious groups.

Estimating the impacts of such a tax policy would be informative to this discussion. To my knowledge, there has not yet been a serious attempt to this end. There are many reasons for this. For some, it is a policy proposal so far removed from being a real possibility that it does not warrant rigorous attention. For those interested, it is a complex and elusive question as I show below. Reliable data on charitable giving to religious groups is rare. Religious organizations such as churches and mosques are not required to file returns with the IRS like other tax-exempt nonprofits (Internal Revenue Service Publication 1828) so there is little systematic information on their finances. State and local tax treatment of nonprofits varies widely.

In this short essay, I attempt to empirically estimate the effects of removing the tax-exempt status of religious groups. For brevity, I use the term "church" to broadly encompass any religious organization that might benefit from tax-exemption whose primary purpose is conducting religious services (e.g. mosques, synagogues, temples). I make three key assumptions to simplify analysis in this hypothetical policy world: only churches lose federal tax exempt status (not auxiliaries or religiously-affiliated charities), all churches lose exemption (not just those out of compliance with civil rights law), and state and local governments follow the lead of federal law. I discuss these in greater detail in section 3. This last assumption is especially important because state and local governments have a great deal of discretion in the incorporation and tax treatment of charities, and allowing for heterogeneous responses to federal policy would dramatically complicate analysis.

The purpose of this essay is not to discuss the moral or constitutional arguments against or in favor a policy that removes the tax-exempt status of churches. That is best left to legislators and tax and constitutional lawyers. Instead, I provide an analysis and discussion of several consequences such a policy might have.

2. Context

It is helpful to discuss the existing tax benefits churches receive to provide a framework for analyzing the policy change. Since the War Revenue Act of 1917, donations to charitable organizations, including churches, have been deductible from taxable income. This is not without consequence for the government's tax revenue (Gravelle *et al.*, 2019), but has been justified by the assertion that charities provide social services for the benefit of the public that encourage social cohesion and reduce government spending on related services. Economists followed the birth and expansion of the charitable deduction with decades of research into the "tax price of charitable giving" to assess whether charitable deductions are "treasury efficient" (a dollar of tax revenue forfeited generates a dollar or more of private contributions to a public good). See Bakija (2013) for a primer on this literature.

Charitable organizations have a favorable tax treatment beyond their donors being incentivized to give by the tax code. Under the Internal Revenue Code (IRC), tax-exempt charities are not required to pay taxes on their income or profits, though they are required to pay social security and FICA taxes (Internal Revenue Service Publication 1828). All 50 states have laws exempting qualified nonprofits from paying property taxes and most also allow exemption from sales taxes (Kenyon and Langely, 2011).

Churches receive additional tax benefits not afforded to other charities. The "parsonage rule" allows ministers to "exclude from gross income the fair rental value of a home provided as part of compensation (a parsonage) or a housing allowance provided as compensation if it is used to rent or otherwise provide a home." This reduces the amount of employment taxes paid by churches and could potentially allow them to pay ministers less money. Additionally, by IRS policy, churches are not required to apply for or register to receive tax exemption and they are exempted from filing Form 990 that is required of other tax-exempt entities. Lastly, the IRS has special (strict) rules limiting their authority to audit churches. (Internal Revenue Service Publication 1828)

3. Data and Methodology

3.1 Assumptions

I evaluate a hypothetical policy world where churches are no longer tax-exempt entities. As mentioned before, this requires simplifying assumptions to make analysis tractable. I first make three key assumptions about the hypothetical policy world that provide the foundation for analysis.

> *Assumption 1: Only religious organizations (churches) lose their tax-exempt status. This does not include religious schools, hospitals, or other organizations who have a primary purpose other than providing or conducting religious services.*
>
> *Assumption 2: All churches lose tax-exempt status, independent of religion, creed, or practice.*
>
> *Assumption 3: All states and municipalities uniformly follow the federal tax treatment of churches.*

To be sure these are strong assumptions. For example, in *Bob Jones University v. United States*, the U.S. Supreme Court ruled that the First Amendment does not protect institutions from having their tax exemption revoked by the IRS if the institution has practices in opposition to a "fundamental national public policy." This set a precedent for an arguably more plausible first step: evaluating the tax-exemption of religious universities that violate civil rights law. This would of course violate both Assumptions 1 and 2. As for Assumption 3, the existing heterogeneity in the state and local tax treatment of nonprofits suggests that states and municipalities would not respond uniformly to a federal policy that removes churches' tax exemption. Areas with a high concentration of religious voters would likely seek to protect the favorable tax status of churches while other states might opt to follow the federal government's lead. Taken together, it is clear how removing these assumptions would quickly complicate analysis.[40]

3.2 Approach and data

I will look at two dimensions that this hypothetical policy might impact: donative behavior (giving) and church revenues and expenses in the United States. In reality these are not isolated realms of behavior and, under this policy, we would expect there to be iterative interaction in the long-run. For example, if donations go down then churches will be incentivized to be more strategic about "making the ask" which could mitigate the reduction in donation income. I focus here on what I can tractably analyze but I acknowledge that such dynamics are important to consider for a holistic understanding of the implications of a policy.

As in Chapter III, I use the Panel Study of Income Dynamics to analyze donor behavior. The PSID is especially advantageous here because it separately records secular and religious giving and includes questions on the religious affiliation of respondents. Religious giving in the PSID is explicitly elicited only for religious institutions – what I call churches here – and not religiously-affiliated charities like hospitals, food pantries, etc.[41] This is crucial in satisfying

[40] For example, if some states maintain tax exemptions for churches, will those states lose eligibility for federal grants? How will federal income taxes account for households who were able to deduct church donations on their state tax return? Will states continue to allow municipalities discretion on how sales and property taxes are levied on churches? Clearly some questions are impossible to answer in advance of a serious legal discussion.

[41] The PSID elicits religious giving with the following: "Did you make any donations specifically for religious purposes or spiritual development, for example to a church, synagogue, mosque, TV or radio ministry? Please do not include donations to schools, hospitals, and other charities run by religious organizations. I will ask about those next."

Assumption 1. For robustness, I include a range of estimates for donative behavior using the "PSID definition" of religious giving and an "expanded definition" of religious giving. For the expanded definition I include a household's reported giving to the "other" category as religious instead of secular. This leaves nine categories of secular giving: youth, art, education, health, international aid, environment, neighborhood/community, basic needs, and combined purpose organizations. The PSID definition only includes reported religious donations as religious; all other giving is considered secular.

Further, as mentioned in Chapter III, the PSID includes giving for both itemizers and non-itemizers which allows me to observe households that never itemize or stop itemizing. It is necessary to include such households to get accurate estimates of how behavior would change across income levels; limiting analysis to itemizers would drastically overstate changes in giving, especially among lower-income groups with very few itemizers.

For simplicity, I restrict analysis to data from the 2017 PSID year (2016 tax year). To approximate policy responses under the most up-to-date tax code, I estimate all tax liabilities as though this policy occurs in 2018 (inflation-adjusting monetary variables). This means the hypothetical policy I analyze is occurring under the tax schedule and deduction rules for the Tax Cuts and Jobs Act of 2017.[42] Federal and state marginal tax rates and tax liabilities come from NBER's TAXSIM. I remove one household that has a state marginal tax rate over 50%, which is implausible and is likely the consequence of a weird notch in the tax code that TAXSIM has difficulty estimating. Similar to Chapter III, I group households by estimated federal adjusted gross income (AGI). Two households with negative AGI and 34 households with AGI over $500,000

[42] As shown in Chapter III, the Tax Cuts and Jobs Act dramatically reduced the incentive, and therefore propensity, to itemize. This further highlights the importance of having data on non-itemizers to conduct this policy analysis.

are removed. I limit analysis to households making no more than $500,000 per year in adjusted gross income because there are not enough observations in the PSID above this level to generate reliable estimates. This leaves me with a final sample of 6,022 households. Table 1 summarizes the AGI bins.

As discussed in Chapter III, the TCJA dramatically reduced the incentive, and therefore propensity, to itemize for most households. This further highlights the importance of having giving data for non-itemizers to conduct this policy analysis. However, this also implies that the benefits of itemizing donations increasingly accrue to higher-income households. Our data does not sufficiently cover households with AGI over $500,000 to draw reliable conclusions, but those are the households most likely to itemize. It is also insufficient to use IRS tax return data (or their summaries, as used in Chapter III): these data do not separately document donations to churches and secular organizations which precludes the exact analysis needed to evaluate this policy. We are left with an ironic data gap. The tax liabilities of donors for which we have solid data are predominately unaffected by changes in churches' tax-exemption, and the necessary data is missing for the majority of donors whose tax liabilities would be impacted by such a policy. Despite this, I analyze how giving behavior will change for households in our data making under $500,000 per year, while acknowledging that this is an incomplete picture and that future research would greatly benefit from more detailed data on high-income households.

I also combine results from the PSID with the National Congregations Study (NCS) from 2012 to try to estimate consequences for churches. The NCS is a nationally representative sample of American congregations, collected in conjunction with the General Social Survey.[43] Face-to-

[43] The 2012 NCS includes an oversample of Hispanic congregations.

face surveys elicit various aspects of respondents' congregations. Respondents are predominantly clergy or staff members – 7% were non-staff congregational leaders. The NCS includes information on the tradition and denominational affiliation of congregations, as well as estimates of the number of regular adult and non-adult participants.

Table 1: Summary of Federal Adjusted Gross Income Bins

Federal AGI	N	Minimum AGI	Maximum AGI	Mean AGI
\$0 - \$20,000	1,762	\$0	\$19,961	\$5,090
\$20,000 - \$30,000	427	\$20,003	\$29,988	\$24,995
\$30,000 - \$40,000	469	\$30,055	\$39,986	\$34,966
\$40,000 - \$50,000	407	\$40,005	\$49,875	\$44,614
\$50,000 - \$75,000	880	\$50,190	\$74,970	\$61,252
\$75,000 - \$100,000	617	\$75,222	\$99,961	\$86,892
\$100,000 - \$125,000	777	\$100,275	\$149,678	\$122,610
\$125,000 - \$200,000	337	\$150,150	\$199,815	\$172,716
\$200,000 - \$300,000	232	\$200,502	\$297,599	\$238,566
\$300,000 - \$500,000	80	\$300,300	\$493,521	\$371,938

Both the PSID and NCS have categories for belief (religion, tradition, denomination, etc.) I condense PSID households into 12 (self-identified) belief categories: Atheist/Agnostic, Baptist, Catholic/Orthodox, Episcopalian, Jewish, Latter-day Saints (Mormon), Lutheran, Methodist, Other Non-Christian, Other Protestant, Pentecostal, and Presbyterian. The majority of these were naturally occurring categories in PSID data – "Other Non-Christian" and "Other Protestant" were necessary catch-all categories to avoid extremely small groups and make analysis meaningful.[44] Unsurprisingly, the set of NCS categories is much larger than the PSID. I consolidate NCS labels

[44] For example, in 2017 the PSID has only 4 households that report being Amish or Mennonite and 1 being Quaker.

of tradition and denomination to fit the same 12 belief categories as in the PSID. This allows me to merge the data sets and analyze financial effects for different types of churches in section 5.[45]

Data on churches is another, arguably larger, hurdle to overcome in assessing this policy. As mentioned above, the IRS does not require churches to file returns (such as Form 990) like other nonprofits that are exempt from taxes.[46] So data on churches' finances – staff compensation, donation receipts, assets, and property – are only available in surveys that ask, which are necessarily subject to inaccurate reporting or intentional mis-reporting. Further, because churches in the United States are disaggregated (not coordinated or governed by a singular entity), data may be differentially available and reliable. For example, a survey of Baptist churches is clearly not representative of Catholic churches or Islamic masjids, and surveys containing detailed information on a broad spectrum of religious institutions are sparse.

4. Donative Behavior

It is most clear to start by analyzing how donors would respond when donations to churches are no longer itemizable deductions. This data is most straightforward and there is a wealth of literature on tax price elasticities (see Chapter III for more discussion on this topic).

There is very little work that separately estimates the tax price elasticity of *religious* giving and *secular* giving, though there is reasonable conjecture that religious people's giving to their churches is relatively inelastic (Eckel and Grossman, 2004; Brooks, 2007; Helms and Thornton, 2012; Thornton and Helms, 2013). Brooks (2007) and Helms and Thornton (2012) both use PSID

[45] Of course, it is problematic to connect reports of congregation sizes from 2012 to giving data from 2017. This is a necessary connection in the absence of more recent, available congregation data.

[46] Churches are required to file returns for unrelated business income (Internal Revenue Service Publication 1828).

data to estimate separate tax prices elasticities and show that religious giving should be considered differently from other types of giving.[47] I use the approach outlined in Chapter III to generate separate elasticities for religious and secular giving using PSID data from 2001 to 2017, similar to Helms and Thornton (2012). I find that religious giving is inelastic (between -0.529 and -0.544) and secular giving is essentially unit elastic, meaning if the tax price of giving increases 10% then giving to churches will decrease by 5.3 – 5.4% and all other giving will decrease by 10%.[48] However, even facing fairly inelastic responses to changes in the price of giving to a church, we may reasonably expect that removing the favorable tax treatment of religious contributions will decrease religious giving for some households.

The question is then *how much* will giving be reduced. There are two parts to this: a reduction in religious giving due to the change in tax treatment and, potentially, a reduction in secular giving due to a change in itemization status or marginal tax rate. When religious giving is no longer itemizable, the tax price of secular giving may also increase for a household, either by shifting them into a new tax bracket or by removing the incentive to itemize altogether.

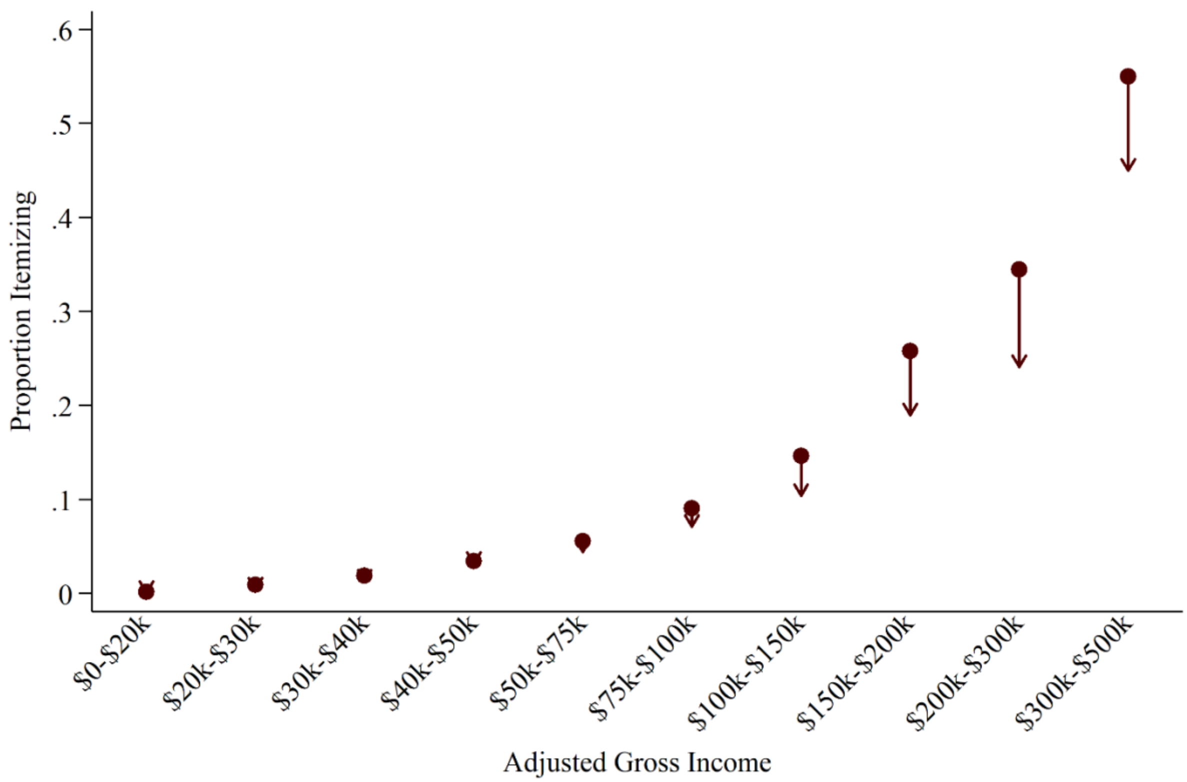
To calculate this change, I first estimate two tax prices: one when all giving is deductible for itemizers and the other when only secular giving is deductible (i.e. the hypothetical policy). I calculate these prices using the same method as described in Chapter III, by observing changes in the estimated tax liability when $100 is added to giving. I estimate that 8% of households itemize when all giving can be included. When only secular giving is itemizable, just 6% of households

[47] The estimation techniques used by Brooks (2007) and Helms and Thornton (2012) are fairly similar: both use the zero-dollar price instrument that is standard in the literature. They accomplish this by regressing religious and secular giving, separately, on the log of the price and control variables. Brooks (2007) breaks down secular giving into several giving categories as well.

[48] Helms and Thornton (2012) find tax price elasticities of religious and secular giving equal to -0.79 and -1.217, respectively. They use the 2001 - 2005 PSID giving data and a different technique to account for nongivers. Our estimates are qualitatively similar.

itemize, meaning 25% of itemizing households only do so because of their religious giving. The changing propensity to itemize is not uniform across the income distribution – higher-income households are both more likely to already itemize and more likely to stop itemizing due to the policy. Figure 1 shows how itemizing behavior changes across AGI groups.

Figure 1: Changes in Proportion of Households Itemizing from Removing Tax Exemption for Religious Donations



To estimate changes in giving to religious and secular recipients, we first break apart how the price of giving changes for each category. As in Chapter III, and following the literature, the tax price of giving for itemizers is $1 - \tau$ and 1 for non-itemizers, where τ is the marginal tax rate faced by a household. This reflects that when a dollar is donated, it reduces taxable income on that dollar by the marginal tax rate τ, so the donation really only costs the donor $1-\tau$. I define the price of religious giving under current standard tax rules ("the standard"), P_R, and under the new policy ("the policy"), P_R', as:

$$P_R = \begin{cases} 1 & \text{if not itemizing} \\ 1-\tau & \text{if itemizing} \end{cases}$$

$$P_R' = 1 \qquad \text{for everyone}$$

and define the standard and policy prices for secular giving as:

$$P_S = \begin{cases} 1 & \text{if not itemizing} \\ 1-\tau & \text{if itemizing} \end{cases}$$

$$P_S' = \begin{cases} 1 & \text{if not itemizing} \\ 1-\tau' & \text{if itemizing} \end{cases}$$

where τ' is the marginal tax rate under the policy. τ' and τ could be different if the change in itemized deductions increases taxable income enough to shift the household into a different tax bracket. This implies that the change in religious and secular prices, respectively, from the standard to the policy can be expressed as:

$$\Delta P_R = \begin{cases} 0 & \text{if never itemized} \\ \tau & \text{if stopped itemizing} \\ \tau & \text{if still itemizing} \end{cases}$$

$$\Delta P_S = \begin{cases} 0 & \text{if never itemized} \\ \tau & \text{if stopped itemizing} \\ \tau-\tau' & \text{if still itemizing} \end{cases}$$

The main distinction between ΔP_R and ΔP_S is for households that continue to itemize under the policy: the religious price goes up by the standard marginal tax rate but the secular price is the difference between the standard and policy marginal tax rates. While this difference could theoretically be non-zero, in reality the vast majority of continuing itemizers do not experience meaningful changes in their marginal tax rate.[49]

Table 2: Changes in the Tax Price of Religious and Secular Giving

Federal AGI	Mean Change in Religious Price	Mean Percent Change in Religious Price	Mean Change in Secular Price	Mean Percent Change in Secular Price
$0 - $20,000	0.00014	0.02%	0.00006	0.01%
$20,000 - $30,000	0.00059	0.06%	0.00019	0.05%
$30,000 - $40,000	0.0025	0.29%	0.00095	0.11%
$40,000 - $50,000	0.0053	0.63%	0.00029	0.03%
$50,000 - $75,000	0.011	1.44%	0.0022	0.28%
$75,000 - $100,000	0.019	2.56%	0.0038	0.49%
$100,000 - $125,000	0.038	5.27%	0.011	1.42%
$125,000 - $200,000	0.068	9.40%	0.017	2.36%
$200,000 - $300,000	0.096	13.57%	0.027	3.79%
$300,000 - $500,000	0.172	25.48%	0.033	5.01%

Table 2 shows the average percent change in tax price for religious and secular giving by AGI group using the normal PSID definition of donations to religious and secular causes. Across all income levels, the price of religious and secular giving increases by 5.87% and 1.35%, respectively, on average. Naturally, the changes in prices are concentrated in higher income bins because those groups have a higher proportion of itemizers. Also, as expected, for every bin the mean percent change in the religious price is higher than the mean percent change in the secular price. This is the direct implication of religious giving no longer being itemizable.

I combine the estimated changes in prices, elasticities, and mean giving by income bin to generate estimates of the change giving shown in Panel A of Table 3. These estimates use the PSID

[49] Only 12 observations have meaningfully different calculated marginal tax rates under the standard and the policy.

definitions of giving. Because there are so few itemizers, not many households face a change in prices and giving doesn't noticeably change until the top two income groups. For example, a household with $200,000 in adjusted gross income is predicted to give about $150 ($200) less to churches (all causes), on average, under the policy. Figure 2 shows this change graphically alongside estimates using the elasticities calculated in Helms and Thornton (2012) for comparison.

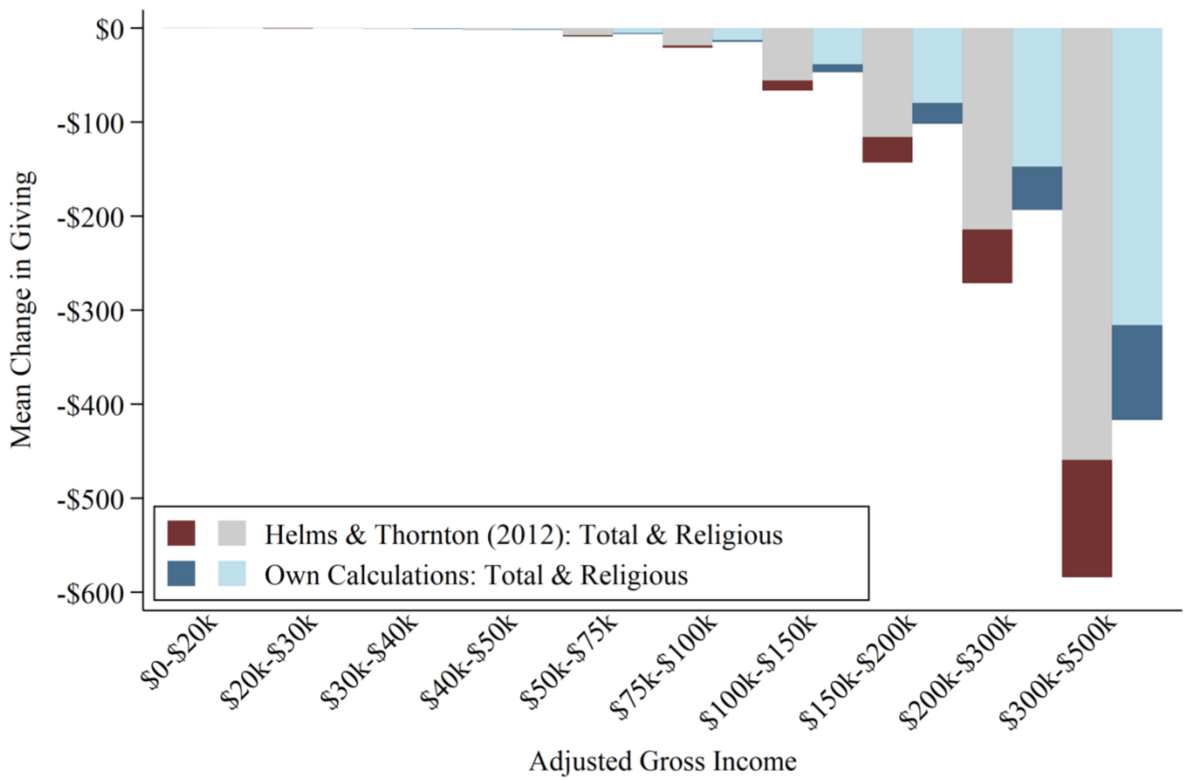
Table 3: Estimated Changes in Giving from Removing Tax Exemption for Religious Donations

Panel A			
Federal AGI	Mean Change in Religious Giving	Mean Change in Secular Giving	Mean Change in Total Giving
$0 - $20,000	-$0.04	-$0.01	-$0.05
$20,000 - $30,000	-$0.11	-$0.08	-$0.20
$30,000 - $40,000	-$0.53	-$0.20	-$0.72
$40,000 - $50,000	-$1.55	-$0.07	-$1.62
$50,000 - $75,000	-$5.40	-$0.92	-$6.31
$75,000 - $100,000	-$12.95	-$1.88	-$14.84
$100,000 - $125,000	-$39.09	-$8.47	-$47.56
$125,000 - $200,000	-$81.12	-$22.27	-$103.39
$200,000 - $300,000	-$149.57	-$47.18	-$196.75
$300,000 - $500,000	-$321.01	-$103.21	-$424.21
Panel B: Scaled-Up Estimates (in millions of dollars)			
Definition of religious giving	Change in Religious Giving	Change in Secular Giving	Change in Total Giving
PSID definition	-$2,292.22	-$603.99	-$2,896.21
Expanded definition	-$2,307.99	-$637.31	-$2,945.29

The "expanded" definition of religious giving is the sum of PSID-defined religious giving and giving to the "other" category, as elicited in the PSID. Secular giving in this expanded definition includes donations to youth, art, education, health, international aid, environment, neighborhood/community, basic needs, and combined purpose organizations.

Panel B shows the estimates from Panel A scaled up by the number of returns recorded in IRS Statistics of Income tables. The entire exercise was repeated for the expanded definition of giving described above to provide a range of estimates. It is notable that the estimates are not very sensitive to small changes in the definition of religious giving. For all households making up to $500,000, I estimate that giving to churches (all causes) would decrease by about $2.3 billion ($2.9 billion); non-church giving would decrease by about $600 - $630 million if donations to churches were no longer tax exempt. This represents about a 1.8% decrease in total giving to religious groups (1% decrease in total individual giving) in 2018 (Giving USA Foundation).

Figure 2: Estimated Changes in Giving, by Adjusted Gross Income



These estimates rest on the (arguably) unreasonable assumption that this once-itemized giving to churches would disappear. In fact, it is very likely that at least some of the itemized donations to churches would instead go to an organization that *is* tax-exempt. At the core of this is a discussion about the substitutability of religious and secular donations: a question we do not really know the answer to. There has not been much of a systematic attempt at understanding how people trade off giving to their church with giving to secular charities, especially considering the nuance of tax incentives.[50] Moreover, if households do substitute their previously-itemized church giving to another type of giving – instead of simply keeping that money – it is not clear what type of charity they will substitute to. It could be a religiously-affiliated or religious adjacent organization like World Relief or the Salvation Army. Or it could be a totally unrelated secular charity like a cancer research center, local food bank, or theatre. This is an open question in the field of economics that would be benefit from more attention.

5. Church Finances

5.1 Revenues

It naturally follows that if donors decrease giving to churches then churches' revenues will decrease.[51] The decrease each church would experience is a function of many factors: the income and wealth composition of congregants, the itemization status of congregants, and the relative strictness of the church (Iannaccone 1988, 1992, 1994). This last point is a consequence of research in the intersection of the economics and sociology of religion: highly sectarian religious groups

[50] One example is Hill and Vaidyanathan (2011), who observe that families increase secular giving when they increase their religious giving. Hungerman (2013) looks at inter-denominational substitution in the aftermath of Catholic sex abuse scandals. Gruber and Hungerman (2008) have the closest attempt at substitution between church and non-church giving: using repeals in "blue laws," they find that church attendance and church giving fall without a comparable decrease in non-church giving. These studies, while important, do not give us a robust understanding of the substitutability of church and non-church giving.

[51]Churches can, and do, have multiple streams of revenue outside donations, including investments, rental income, and income from the sale of property, as well as unrelated business income which is taxed. Behavior around these sources of income would also be likely to change in the event of a policy that required reporting (Oxley, 2020) or otherwise altered their tax treatment. I focus analysis here on donation income, but another fruitful area of research is to analyze these other revenue streams.

institute strict behavioral rules to reduce free riding on the group public good, which results in stronger adherence to group norms, including donative behavior. Iannaccone (1988) shows that such groups are especially appealing for lower-income households. Relating to section 4, such "strictness of belief" can be thought of as individual churches creating a norm of highly inelastic price elasticities of giving. I do not have the ability in the present data to observe churches' beliefs with sufficient granularity to control for or explicitly test these heterogeneous norms. This, again, is another fruitful area for additional research.

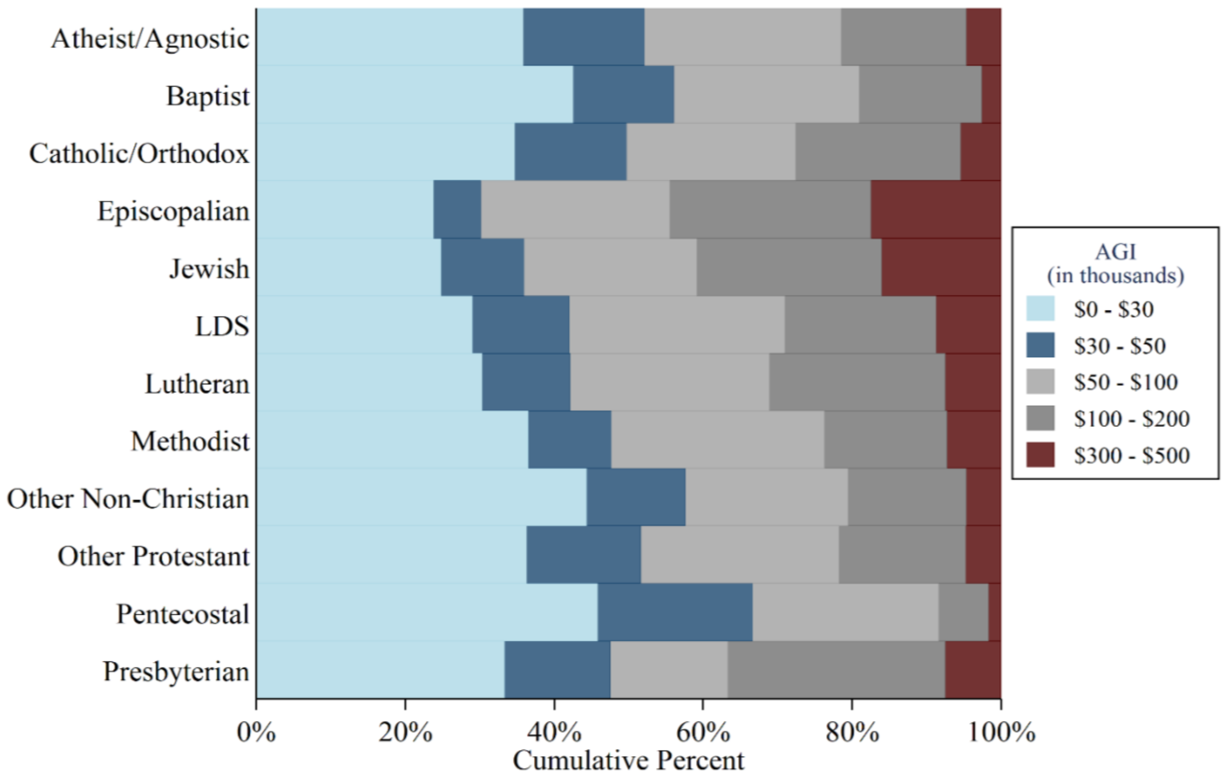
As mentioned before, publicly available data on churches is difficult to come by. This is especially true for data that contains measures of the income and wealth distributions within a church alongside survey questions that could give a measure of "church strictness." In the absence of such data, I use the self-identified religious preferences for the recorded household head in the PSID to group donors by belief (see section 3.2 for more details).[52] I estimate the adjusted gross income composition within each belief group, which allows me to apply the average changes in giving from section 4 to observe how belief groups will be differentially impacted by the hypothetical policy. To avoid hyper-granular estimates, I use five AGI bins for this section of analysis, instead of ten as before. This protects me from having a belief-income group with, for example, 5 households. Figure 3 shows the proportion of households in each belief group that fall into these estimated federal adjusted gross income groups.

On average, people who identify as Episcopalian or Jewish tend to be higher income while Pentecostals and Baptists are lower income. For example, 27% of self-identified Episcopalians

[52] Masci (2016) writes on the Pew Research Center's findings using the 2014 Religious Landscape Study to measure the income make up of over 20 belief groups. However, they use family income instead of AGI which precludes me from applying my estimates from section 4 to look at the impact on belief-group revenues.

have a calculated AGI between $100,000 and $200,000, compared to 16.4% of Baptists and 6.7% of Pentecostals. It is important to note that these are not congregation-level estimates – these are "belief group" estimates. There could be (and likely is) considerable heterogeneity across congregations within belief groups in both the income distribution and relative strictness of norms.

Figure 3: Distribution of Federal Adjusted Gross Income, by Belief Group



In the absence of more detailed data on the heterogeneity of individual congregations, I estimate changes in giving for a "typical" congregation in each belief group. I use the NCS to calculate the median size of a congregation for each belief group.[53] Combining the congregation

[53] Churches sizes are subject to skewness, making the mean congregation size significantly larger than the median.

size with the estimates of the income distribution within belief groups (Figure 3) and the estimated changes in church giving for each income group (Table 3, Panel A), I approximate how donation receipts will change for the "typical" or "median" congregation in each belief group. The results are displayed in Table 4.[54] Naturally, I omit Atheist/Agnostic from this analysis because they are not recorded in the NCS as having congregations. For simplicity and tractability, I assume that the median congregation in each belief group has the average income distribution shown in Figure 3.

Table 4: Estimated Change in Giving to Churches, by Belief Group

Belief Group	Median Number of Regularly Attending Adults	Estimated Change in Giving	Estimated % Change in Giving
Baptist	150	-$2,723	-2.58%
Catholic/Orthodox	1075	-$29,949	-3.45%
Episcopalian	233	-$13,701	-5.43%
Jewish	250	-$13,495	-5.27%
LDS	135	-$4,717	-4.01%
Lutheran	175	-$5,931	-3.87%
Methodist	110	-$3,216	-3.64%
Other Non-Christian	110	-$2,453	-3.09%
Other Protestant	160	-$3,773	-3.12%
Pentecostal	133	-$1,373	-1.77%
Presbyterian	200	-$7,249	-4.07%

Of course, larger congregations will experience a greater drop in giving because there are simply more people whose giving will be affected by the policy. I estimate that the median Catholic or Orthodox church would experience about a $30,000 (3.5%) decrease in donations as a result of this tax policy. On the low end, the median Pentecostal church would only see donations decrease by about 1.8%. To be sure, these estimates are flawed. Out of necessity they depend on the large

[54] Because I condense AGI bins between Tables 3 and 4, mean changes in religious giving per household for each bin must also be condensed. I take the average of the changes from Table 3 Column 2 for each combined bin (e.g. $0 - $30,000 gets an estimated average change in religious giving of 8 cents).

– and unrealistic – assumption that the median congregation contains the average income distribution shown in Figure 3. In reality churches within belief groups are likely much more heterogenous in their congregation's income makeup. Some churches have a high concentration of high-income households while others have a high concentration of low-income households, even within belief groups in similar geographic areas. Churches will experience greater (lower) decreases in donation income if their congregants are more homogeneously higher (lower) income. This logically follows from Table 4. If a larger proportion of a congregation makes above $200,000, more households in that church will experience a decreased tax incentive to donate and that church will experience larger corresponding decreases in donation income, even accounting for the inelasticity of church donations. This implies that the hypothetical policy would differentially impact churches and could theoretically not cause a noticeable decrease in donation income for predominantly low-income churches. Further, the NCS reports the number of *participating* adults in each congregation sampled. This is not necessarily the number of members or even givers. The set of donors within a congregation could indeed be smaller than the set of participants.

5.2 Expenses

Turning to churches' expenses, we have even less reliable data with which to make specific, informed conjectures about the consequences of the policy. Churches are not required to file Form 990 with the IRS like other tax-exempt nonprofits. This means there is not a systematic way to assess the assets or expenditures of churches aside from surveys, which are rarely gathered in a way that is nationally representative while also containing the detail necessary. The lack of data makes analysis speculative, even for government agencies (Kenyon and Langley, 2011; Gravelle and Sherlock, 2009). Still I attempt to provide broad, rough estimates of how churches would be affected, with the above-mentioned data problems as a caveat.

There are two dimensions of the hypothetical policy for churches expenses: changes in federal tax treatment and changes in state and local tax treatment. Under Assumption 3, all state and local governments will remove the tax-exempt status of churches in the hypothetical policy world. Relaxing this assumption introduces a great deal of complexity to analysis, which is discussed below. I discuss each dimension in turn.

5.2.1 Federal

As mentioned in section 2, churches get multiple benefits from federal tax-exemption. They are exempted from paying taxes on donation income and other income sources that are related to their "business" – unrelated business income is subject to special tax rules (Internal Revenue Service Publication 1828). The ministers housing allowance permits churches' ministers (broadly defined) to omit the fair market value of their home or a geographically-appropriate housing "stipend" from their gross income. Gravelle *et al.* (2019) report that in fiscal year 2019, the federal government forewent $700 million in tax revenue due to the ministers housing allowance exclusion. In relative terms, that amount is quite small: the housing allowance exclusion constituted just 1.5% of federal individual charitable tax expenditures. For comparison, deductions for charitable contributions to educational institutions constituted 15.6%.

Removing churches' tax-exempt status would also remove this housing allowance deduction. Some or all of the money that was distributed as a housing allowance must be moved to taxable income, which necessarily means ministers' gross income is higher and therefore their after-tax income is lower. Churches could permit their ministers' take-home pay to drop or they could increase their salary to mitigate the loss, which would require increasing their expenses. Salary data for ministers is notoriously ambiguous so it's entirely unclear how to predict if, how many, or how much churches would increase compensation for their ministers in light of a policy that ended the housing allowance deduction. However it is clear that removing this specific deduction would increase federal government tax revenues by $700 million (at least, it would have in 2019) and the additional burden on churches' expenses is likely quite small.

Taxes paid on donation income would much more drastically increase churches' expenses and decrease their after-tax income. However, it is not clear what tax rules would be applied to churches when removing their tax exemption (e.g. corporate tax rates). As an upper bound, we can assume churches are taxed the top corporate tax rate for federal income taxes. Then for each dollar received by a church, their expenses would increase by 21 cents (assuming away the various vagaries of the corporate income tax code). Calculations aside it is straightforward to understand how this will impact churches: they will pay more in federal income taxes than they do now which will increase expenses, all else equal.

5.2.2 State and Local

One of the largest benefits for nonprofits from their tax-exempt status is not having to pay property taxes (Kenyon and Langley, 2011). Churches especially hold a nontrivial amount of property that goes untaxed by state and local governments. Under current tax law, state and local governments have the ability to exempt nonprofits from sales and property taxes, which virtually all do. The amount of foregone sales tax and state income tax revenue for nonprofits is significantly smaller than the amount of foregone property tax revenue on average (Kenyon and Langley, 2011). This is conjecture, of course, because there is little systematic data on foregone tax revenue at the state and local level, in part due to the heterogeneity in local tax policies. For example, even within California the sales tax rate is 7.25% but can be as high as 10.25% in some localities.

As in section 5.2.1, where data lacks conjecture abounds. To get a general idea of how significant the sales tax exemption is I look to Table 16 in Gravelle and Sherlock (2009), which estimate that nonprofits were exempted from $3.3 billion in sales taxes in 2008. This is not only churches though: Table 4 of Gravelle and Sherlock (2009) reports that 21.64% of registered charities were categorized as “religion related, spiritual development.” Directly applying this percentage to the sales taxes exempted, I estimate that churches were exempted from about $714 million. This is of course a very rough estimate that makes several assumptions about the distribution of local tax rates and churches, the purchasing behavior of churches, and more. In addition, churches are not required to register with the IRS, so the “percent registered” estimate is likely incorrect as well. As such, these estimates should be taken as highly speculative.

However, it is reasonable to assume that if churches were required to pay sales and state income taxes, their expenses would increase and they would likely purchase less because the relative price of goods consumed by the church is increasing. It also follows that churches in states with lower sales tax will be less affected and therefore will experience smaller changes in demand and smaller increases in expenses. So, while the exact magnitudes of changes remain an open question until better data is made available, it is clear that church expenses would increase heterogeneously across geographic locations.

Following from the assertion by Kenyon and Langley (2011) that property tax exemptions are higher than sales and state income tax exemptions, it seems clear that requiring churches to begin paying property taxes will have the largest impact on their expenses. It is difficult to estimate precisely how much property is owned by nonprofits, let alone churches, so foregone property taxes are similarly difficult to estimate.

To get a rough idea of exactly how much churches are exempt from paying in property taxes, I look again at Table 16 in Gravelle and Sherlock (2009). They estimate that state and local tax subsidies for *all nonprofits* via property tax exemptions totaled between $17 billion and $32 billion in 2008. The breadth of this range reflects how difficult it is to accurately estimate foregone property tax revenue. They also note that "Property tax estimates were increased 33% to account for religious property." Using this 33% adjustment, I back out how much their property tax exemption estimates were inflated to account for churches. This evaluates to churches across the U.S. being exempted from between $4.2 billion and $7.9 billion in property taxes in 2008. Brauer (2017) uses the NCS to estimate that there were about 414,000 in 2006 (which declined to 384,000 by 2012). Then using the number of churches in 2006 and property tax exemptions in 2008, I get the (very) rough estimate that the average church saved between $10,000 and $18,000 by not paying property taxes in 2008. Of course, not all churches own their building and some churches own vast amounts of property, so this average also reflects the skewness of property ownership among churches.[55] Regardless, it is clear that churches that own their building would see their expenses increase significantly.

Despite the data difficulties documented in this section, it is clear that increases from state and local taxes on sales and property would significantly increase churches' expenses. A related, vitally important question is the distribution of how these expenses would burden churches. For example, relatively richer churches (with more donation income) are more likely to own property

[55] As one example, in 2010, Lakewood Church in Houston, TX bought its property for $7.5 million (Houston Chronicle).

so they will be more strongly impacted by policy requiring the church to pay property taxes. Low-income churches – who may be less likely to own their building – would not experience the same expense increase from property taxes. These churches would, however, still need to pay taxes on donation income, a non-trivial expense increase.

6. Discussion and Summary

6.1 Relaxing Assumptions

Section 3.1 outlines three assumptions to make analysis more tractable. However, it is very likely that these oversimplify the real environment in which such a policy might occur. I briefly consider the implications of relaxing each assumption in turn.

Assuming that only "churches" lose tax exemption is definitionally problematic because religious organizations are variable in structure. Churches often serve multiple purposes. For example, a church may operate a soup kitchen out of its building which could be encompassed under that churches' operations or legally separated as a distinct entity. In the former, the soup kitchen is part of a church; in the latter, it is not. There are also religiously-motivated nonprofits that are not churches, such as the Salvation Army or World Relief.[56] Further, parachurch organizations such as campus ministries and evangelistic missions agencies that operate separately from churches also provide religious services, and church associations and conventions (e.g. Southern Baptist Convention) provide religious support, but are distinct from houses of worship. It's also unclear if (and how) churches would try to restructure because of the policy, becoming registered "secular" nonprofits organized around the charitable aspect of their mission. Under such

[56] While in some locations the Salvation Army is organized as a church, in others it is a registered 501c3 more similar to a secular charity.

a scheme the religious services would be included as another component of their activity but their primary purpose – at least legally – would be their charitable work. This is of course pure speculation and is a product of the legal structure of the policy as much as churches' behavior.[57] It logically follows that the more expansive the definition of religious organization, the larger decreases in giving and charitable activity we would observe.

An additional complication is the treatment of areligious (e.g. secular humanist) organizations. Such groups are not organized around a religious belief, but around a lack of a religious belief – a philosophy. Yet a policy that retains such groups' tax exemption tacitly favors a belief system (one that actively disavows religious belief).

Because it is not straightforward to define a religious organization, it is not straightforward to understand how a policy would be designed to remove tax exemption for religious organizations. One solution is to not remove tax exemption for all religious (and areligious) organizations but only those which are in violation of the law – namely, civil rights law. This relaxes the second assumption described in section 3.2. As mentioned above, this is arguably a more plausible way the tax treatment of religious organizations would develop, because there is already precedent from cases against religious schools like *Bob Jones University v. United States*. Under such a policy, nonprofits may retain their tax-exempt status if they are in compliance with federal law; those not in compliance – for example, by racially discriminating in hiring or refusing to marry same-sex couples – would lose their tax exemption.

[57] Churches could not legally reorganize as "clubs" under, for example, section 501(c)7 without undergoing dramatic changes in activity: most other forms of nonprofits in section 501 require a degree of exclusivity that is antithetical to most church operations.

A policy like this would be both legally and analytically complex. This would necessarily mean all churches must register as nonprofits with the IRS to receive exemption so that *some* may lose it when they violate the law. Implementation (i.e. determination of exemption) would either need to be on a case-by-case basis (as legal violations occurred) or pre-emptive: the IRS determines in advance if a religious organization can be tax-exempt based on whether their stated beliefs align with civil rights law. It is clear how this quickly becomes complicated. Heterogeneous treatment of religious organizations makes it much more difficult to predict the policy's impact on churches and religiosity.

Take as an example Christian beliefs on homosexuality: there is a wide range of perceptions, beliefs, and actions even within church networks that are evolving over time. Accurate estimation would require an understanding of the distribution of beliefs on various dimensions of Christian treatment of homosexuality (participation, leadership, employment, marriage, etc.) alongside information on church size, income makeup, and tax rates. This data is virtually nonexistent. There is the additional complication of dynamics: churches that were once uncertain or mixed in belief (e.g. about same-sex marriage) may converge more firmly onto a doctrine, which could change their congregation's composition as people respond to the change in beliefs. However, regardless of the implementation, allowing churches that are in compliance with civil rights law to be tax-exempt will mitigate the decrease in giving and church activity because the set of affected churches is smaller.

As mentioned above, there is a high degree of heterogeneity in income, sales, and property tax rates. Allowing for state or local governments to independently decide on enforcing tax exemption for religious organizations (i.e. relax the third assumption above) would likewise complicate analysis dramatically. It is also unclear how such interactions would work between government levels.[58]

It is plausible that heterogeneous implementation would follow the concentration of religious belief. States or municipalities with high concentrations of religious citizens would be pressured to retain tax exemption for churches; areas with a majority nonreligious population would likely not. While it is clear that the above-estimated changes would be mitigated if some churches retained tax-exemption, it is not at all straightforward to accurately estimate the distributional impact of the heterogeneous beliefs and taxation.

6.2 Summary

I estimate how a policy that removed the tax-exempt status of religious organizations would impact donations, churches' revenues, and churches' expenses. I show that donations to churches will drop if they lose their tax-exempt status. This is driven by the increased tax price associated with those donations. Approximately 25% of itemizing households would stop itemizing if they could no longer include their religious contributions. I also show that the consequences of this decreased giving are heterogeneous across belief groups. Within belief groups, I reason that churches with higher concentrations of high income households will experience a greater shock to donation income because these congregants are more likely to experience tax price changes, though I cannot show this empirically due to a lack of available data. I estimate that secular giving will also decrease, though not to the same magnitude as religious giving, because households experience a change in their tax price of secular giving when religious giving is no longer itemizable.

58 For example: if a state retains tax exemption for churches, would that affect their federal funding? Can households include their state taxes on their federal tax returns if they were adjusted with donations to churches?

Despite a sever lack of data on churches' revenues and expenses, I attempt to estimate how they would be impacted by losing their tax-exempt status. Donation income would decrease in accord with the previous paragraph. There would be an increase in federal income tax expenses as donation income becomes taxable. At the same time, churches would start paying state and local taxes on purchases, income (in some states), and property. I discuss how paying property taxes would be especially burdensome for churches, primarily for churches that own large amounts of property. These estimates are greatly inhibited by insufficient data – they should be viewed at most as suggestive evidence in the direction of an effect, not certain claims about the magnitude of changes in church expenses. The uncertainty should also be motivation for more reliable data and more rigorous research in this area.

Taken together, if churches lost their tax-exempt status, most would likely experience a decrease in donation income with a simultaneous, significant increase in their expenses. This is of course subject to a great deal of heterogeneous church characteristics. Churches with congregants that are primarily low-income would not experience a significant loss in donation income because very few households in the congregation would have different tax incentives to give. Similarly, these churches are probably less likely to own property which means they would not experience the large increase in property tax expenses. That does not imply immunity from the impacts of the policy but the effect could certainly be muted.

I believe this topic warrants more empirical investigation. There are many constraints to effectively estimating the consequences of removing churches' tax exemption, primarily the limited availability of data. Access to better data is crucial for government agencies and researchers to generate meaningful predictions about such a policy. There are several related questions that researchers could address in the meantime, including the substitutability of religious and secular giving, separating tax price elasticities of religious and secular giving, and estimating the distribution of churches' "strictness" of belief in the U.S. and what that implies for their responses to relevant policy.

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CHAPTER V

CHARITY BEGINS AT HOME:

A LAB-IN-THE-FIELD EXPERIMENT ON CHARITABLE GIVING[59]

1. Introduction

Charitable organizations vary along many dimensions, including their geographic level of operation. Organizations can operate at an international, national, state-wide, or local level. It is unclear, however, whether and how donors differentiate between charities at different levels that have similar missions. Do donors consider the reach of the charity and direct impact of their donations? Do they prefer to donate to a local organization where they will have a concentrated impact, or to a larger organization with broader reach? Little is known about how donors make tradeoffs between organizational characteristics in making their donation decisions. This study addresses this question by conducting controlled, lab-in-the-field experiments where subjects make real donation decisions to charitable organizations from a fixed budget.

In this paper, we report the results of a comparative dictator game (CDG hereafter) experiment conducted in two Texas towns. Our study systematically varies the organizational level, including national (N), state (S), local (L), and individual person (P) organizational levels. Specifically, we use a series of dictator game (DG) decisions. Subjects make four separate allocation decisions, distributing a fixed endowment between themselves and a charitable recipient at each of these different levels. One is selected randomly for payment. In a separate game, the

[59] Previously published with C. Eckel and R. Wilson in *Games*, 9(4), p. 95.

selected dictator game (SDG hereafter), we ask subjects to indicate which of the decisions they would most like to implement.

A considerable body of research uses lab experiments to study charitable giving. The superior control of the lab provides an ideal methodology for addressing the impact of fundraising practices, examining motives for giving and testing theories of altruism (Vesterlund, 2016). Even though the decisions made in lab experiments are "real donation" decisions (Eckel and Grossman, 1996), they have been criticized for their use of convenience samples of undergraduate students. In this study we retain the control of lab-type protocols, but recruit a random sample of adult subjects. This allows us to test the effect of the level of the organization in a tightly controlled setting, but with a broader sample of participants. This methodology is ideally suited to the research question. Indeed, the question cannot be answered with observational data, as no data are available that show such tradeoffs at the level of the individual decision maker.

We are not the first to use a comparative approach to examine variations in dictator-game giving. For example, Candelo *et al.* (2019) used a CDG experimental design to test the effect of recipient characteristics on donations in adult populations. They found that people increase giving to more "worthy" recipients, such as people with disabilities, single mothers, and people with more children. Candelo *et al.* (2018) include an appendix describing the initial development of the CDG using lab experiments. Others, like Fong (2007) and Fong and Luttmer (2009) vary specific recipients in dictator games to assess biases due to race or need.

The work most similar to ours is Li *et al.* (2011), where the authors use federal, state and local levels in their study of dictator giving to government organizations in a lab experiment with a student sample. They find that subjects have a preference for the mission and geographic level of operation. People were more likely to give a non-zero amount towards cancer research and disaster relief than education enhancement and parks and wildlife. Furthermore, giving monotonically increased in operation level (national > state > local) for disaster relief organizations (but not all missions).

Our study focuses on disaster relief work by private charities and differs from Li *et al.* (2011) in two important ways: We use adult participants in the field, and we add an additional recipient—an anonymous individual in the subjects' town. This is the first study to vary the levels at which charities operate in a sample of adult participants, and to include an individual in the decision set. This allows us to ask whether adults embedded in a community differentiate giving among charity-levels while also considering giving to an individual. These differences motivate our hypotheses in Section 2.1.

We find that subjects give more to an anonymous person than to any of the three charitable organizations in the CDG, consistent with prior literature discussed in more detail below. Similar to Li *et al.* (2011), we find that dictator giving to a national organization is higher than to a state organization. Contrary to Li *et al.* (2011), however, we find that average donations by community members are higher to local organizations compared to state organizations and statistically equivalent across national and local organizations. This creates a U-shaped revealed-preference giving curve across levels, which is verified by subjects' selections in the subsequent SDG. We explore how this behavior correlates with socio-demographics and measurements of trust in people and in institutions. We also discuss possible explanations for why our findings contradict those of Li *et al.* (2011).

2. Experimental Design and Implementation

2.1. Hypotheses

As described above, Li *et al.* (2011) find that giving to disaster relief monotonically increases with the level of operation. This is a surprising conclusion, given the extensive charitable giving literature around directed giving (Eckel *et al.*, 2017; Li *et al.*, 2015) and the identifiable victim effect. The identifiable victim effect, described in the charitable giving literature, is the tendency of donors to give more when a single recipient is identified. This is because they are an "identifiable" instead of a "statistical" victim (Jenni and Loewenstein, 2003). Even a weak form of identifiability, without accompanying information, can increase caring (Small and Loewenstein, 2003). For a meta-analysis of the identifiable victim effect, see Lee and Feeley (2016).

When making contributions to a charity, we propose that donors in the CDG consider both the reach of an organization and the direct impact of their contribution, as well as the potential tradeoff between them. For example, national charities have a broader reach than local organizations, and may be better able to allocate funds efficiently, where they are most needed. This is a potential explanation for the behavior observed in Li *et al.* (2011). Yet a single contribution has a very small impact on national-level needs. By contrast the reach of a local charity is much narrower, but a contribution can have a much higher relative impact. At the most extreme, a contribution to a person has the most impact, but the narrowest reach.

All of the charities we use service anonymous victims. To make our "identifiable victim" comparable, we keep that person's identity anonymous. This allows us to better test whether impact and reach come to mind when people consider their contributions. We expect individual recipients to receive the largest amount, from which we can conclude that subjects value impact over reach. This forms our first hypothesis:

> *Hypothesis 1: When presented with separate giving decisions to national, state, and local organizations and an anonymous individual, subjects give more to the individual than to any other level.*

Impact and reach surely interact with each other differently when donors consider where and how much to give to organizations instead of identified individuals. Since each of the decisions in our CDG is independent, we propose that subjects consider the charities differently. We therefore use the results of Li *et al.* (2011) – subjects' revealed preference rank of charity level (national > state > local) – to form our second hypothesis:

> *Hypothesis 2: Beyond giving to the individual, subjects' donations will be monotonically increasing with the level of the organization's operation.*

We believe this result from Li *et al.* (2011) arises because the relative impact of a donation beyond an individual becomes either less important or less clear, so subjects will switch to considering an organization's reach. Our experiment is not designed to pull apart these two possible mechanisms; however, we propose that, in a comparative-statics analysis, preferences for the reach of an organization are mediated by prior beliefs about the relative effectiveness of aid at a given level (national, state, or local). We therefore expect some measurement of beliefs about trust in institutions (operating at the state or federal level) or trust in people (focused locally or an individual) to have a statistically significant correlation with giving behavior across organizations. Running this experiment with adults—particularly adults who have experienced natural disasters—is therefore valuable because we expect their beliefs to be more developed and informed than student subjects who may or may not have experienced natural disasters. This forms two additional testable hypotheses:

> *Hypothesis 3a: Trust in institutions, as a proxy for beliefs about the effectiveness of aid at national and state levels, has a significant effect on giving to national and state charities. Furthermore, trust in people, as a proxy for beliefs about the effectiveness of aid at the local level or to a person, has a significant effect on the giving to the local charity and the individual recipient.*

> *Hypothesis 3b: Age is significantly and heterogeneously correlated with giving amounts at each level.*

Because we cannot a priori state how beliefs about organization level effectiveness change with age or trust in institutions or people, we remain agnostic on predicting the direction or magnitude of these coefficients. We simply hypothesize there to be heterogeneous preferences for organization level by age and trust measurements.

When making the second decision (the SDG), subjects have already selected their contribution level for each organization. They were unaware of the SDG when making the CDG decisions. In choosing which CDG decision they prefer, subjects reveal which recipient they prefer to give to among the four possibilities, conditional on the amounts they have allocated to each. For example, when forced to make a decision about how much to give to each charity, subjects may choose different amounts depending on the perceived benefit of the contribution. However, when asked to choose, a subject might prefer to avoid their more generous decision, and instead opt for the one where they gave the least. Indeed, this is what Candelo *et al.* (2019) find in a low-income, high minority population with a similar experimental design: subjects allocated the most to the 'most worthy' recipients, but subsequently chose in the SDG the recipient to which they gave the least in the CDG. This informs our final hypothesis:

Hypothesis 4: In the selected dictator game, the majority of subjects will choose the recipient to which they sent the least in the comparative dictator game.

This argument has some of the same flavor as work on "avoiding the ask" in charitable giving. DellaVigna *et al.* (2012) place flyers on door knobs with a return time for solicitation, allowing households to seek or avoid the fundraiser. The flyer reduces the number of people opening the door, effectively "avoiding the ask". Andreoni *et al.* (2017) placed Salvation Army bell ringers near entrances at a mall around Christmastime, experimentally altering the difficulty of avoiding the ask. Making avoidance difficult increased donations. In comparison, we give subjects the option to 'avoid' implementing the previous CDG decisions. This decision allows us to further uncover their preferences for giving.

2.2. Sample and General Study Design

The real-donation dictator game was embedded in a larger study[60] carried out in 2010 in two Texas towns whose primary focus was on natural disaster preparedness. The study included survey components and lab-in-the-field incentivized decisions. The 2010 data collection was the second wave of a multi-year study. Subjects were originally recruited in 2009 and participated in a series of incentivized decisions to elicit standard economic preferences. The second wave of the study was carried out between 14 April 2010 and 14 June 2010. A total of 310 subjects participated in this wave. The study was conducted in two communities (population < 20,000) that were selected based on their risks from natural disasters and for their comparability in terms of the local economy and the characteristics of their citizens.

[60] This study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Institutional Review Board of: Rice University, 09-0674X, approved 26 May 2009; University of Texas at Dallas, MR09-51, approved 29 May 2009; and Texas A&M University, IR2013-3020, approved 6 May 2013.

In each community, we recruited a sample of adult residents from specific neighborhoods that were matched according to demographic characteristics (income, employment status, and age) using census data. For the 2009 wave, recruiters were given a random sample of households in the neighborhoods based on tax parcel information. Participants were contacted at their homes and asked to participate in a study that included a decision-making component and a survey. In order to augment the initial random sample, we used a snowball sampling strategy, asking subjects who participated to help recruit others in their neighborhood.[61] Subjects signed up to participate in a specific experimental session. These sessions averaged 15 subjects and lasted approximately 2.5 hours. Sessions were conducted at a local community center by researchers from Rice University and the University of Texas at Dallas. Participants were paid $20 for completing the survey and could earn additional money for incentivized decision-making tasks; average earnings were $80.

To accommodate different levels of education among the subjects, instructions and protocols were designed to be as simple as possible. Subjects had ‘booklets’ with visual images to aid instruction, and subjects were instructed using posters with the same images. Experimenters followed a script, and walked through each possible decision and the monetary consequences of the decisions. Subjects completed seven different tasks in a fixed order with no feedback. The first task elicited risk preferences using the gamble-choice task adapted from (Eckel and Grossman, 2008). The second task had subjects making choices between amounts they would prefer to receive either in a week or in six months (a time discounting task). The third and fourth tasks were variations on the trust game (Berg *et al.*, 1995). Tasks five and six are the concern of this paper,

[61] Each participant was given two cards containing information about the study, along with a code number identifying the participant, and told to give these cards to their neighbors. They received a $20 bonus for every new recruit (up to two). A total of 51 additional subjects were recruited in this manner.

and consist of two variations on the dictator game, as described below. Of these six tasks, one was randomly selected for payment, using a transparent randomizing device: one subject selected a sealed envelope from a clear plastic tub containing many sealed envelopes, each containing one of the tasks. Everyone in the session was paid for the task that was selected, and subjects received feedback (learned the outcome) only on that task. At the end of the experiments, subjects completed the final task, a survey collecting demographic information and household characteristics, as well as survey measures of trust in institutions and other attitudinal questions. These booklets and surveys were checked for completeness by an experimenter and each individual was privately paid and debriefed.

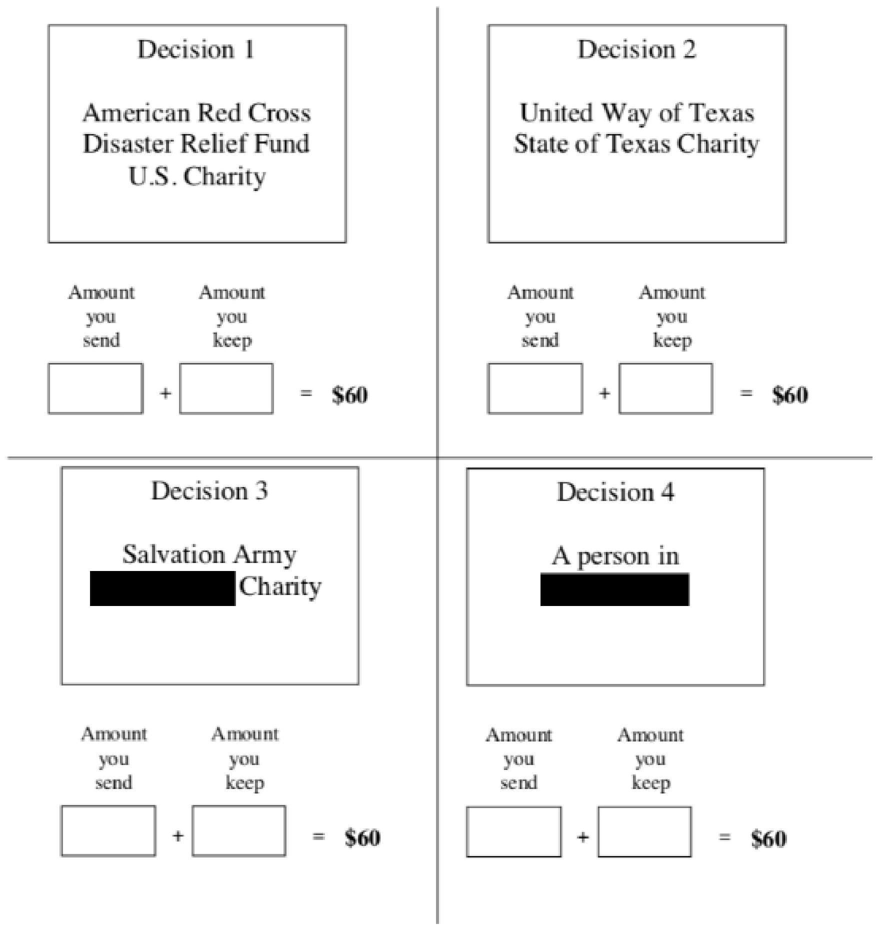
2.3. Dictator Game Designs

In the first of the two dictator game tasks, Task 5 (CDG), subjects were asked to make four separate allocation decisions, dividing $60 between themselves and an organization or individual. (see Figure 1). As shown in Table 1, the four target organizations were the American Red Cross Disaster Relief Fund (national level), the United Way (state level for town 1, local level for town 2), the Salvation Army (state level for town 2, local level for town 1) and a person in the town who was a victim of a fire, identified by the local fire department (individual).

Table 1: Recipient Organizations in the Comparative Dictator Game

	National	State	Local	Person
Town 1	American Red Cross Disaster Relief Fund	United Way of Texas	Salvation Army of town	Individual selected by local fire department
Town 2		Salvation Army of Texas	United Way of town’s county	

Figure 1: Comparative Dictator Game Decision Sheet



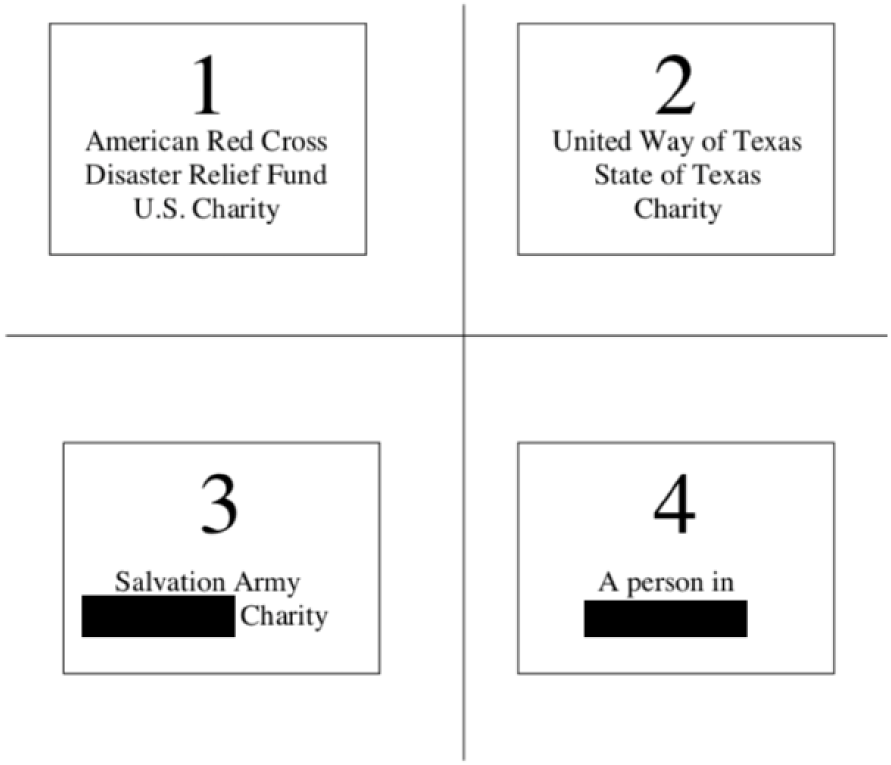
Decision sheets used by subjects when deciding allocations between themselves and charities in the Comparative Dictator Game. References to town are blacked out for confidentiality.

Since we list different organizations at each level, it is possible that heterogeneous giving preferences across levels are actually heterogeneous giving preferences across organizations. To help mitigate this, we block the state and local charities (see Table 1). More importantly, the decision for each organization was framed around disaster relief during the experiment. An excerpt from the instructions given at the beginning of the experiment and Task 5, which included descriptions of the organizations that make their disaster relief work salient, is included in Appendix C. With this very specific frame, we believe that subjects were more likely to be considering the effectiveness of disaster relief at each level rather than the organizations' ability to implement disaster relief or the relative importance of disaster relief in the organization's portfolio.

Subjects were told that if the task was chosen for payment, then, at the time of payment, the subject would randomly choose from four cards indicating the four possible decisions. The decision for the organization on that card would be implemented. Subjects were told that a check would be written to the recipient and were invited to watch the check being written, placed in an addressed envelope addressed, and taken to the nearest mailbox. In the event that the fourth decision was chosen a member of the research team would deliver the check and the recipient's identity would not be revealed. Instructions describing the experiment's payment process is included in Appendix C.

In Task 6 (SDG) subjects were asked to choose which of the four decisions from Task 5 they would prefer to be implemented. These choices are given in Figure 2. Subjects were reminded that they had just made four allocation choices. They were told that if this task was selected for payment, the decision they choose would be implemented. The goal of this task was to see if subjects had a favored charity from the fixed list that we provided them. Subjects merely had to circle one of the decisions.

Figure 2: Selected Dictator Game Decision Sheet



Decision sheets used by subjects when deciding which charity from Task 5 to choose as the sole recipient in the selected dictator game. References to town are blacked out for confidentiality.

3. Data and Aggregate Results

We pool subjects from the two towns in our sample (pooled n = 310). We create a panel data set using each of the subjects' four allocation decisions for analysis. The pooled sample is 58% female, predominantly white (64%), with 36% having "high" church attendance (at least once a week). Hispanics are the second largest racial group (26%). The average age of our sample is 45. Our participants are mostly low income and have low education—55% report earnings below $30,000 per year and 43% have no college education. Table 2 describes in detail the socio-demographic composition of our sample.

Table 2: Summary of Demographic Variables

	Observations	Mean	Standard Deviation
Male	129	0.418	0.494
White	200	0.645	0.479
Hispanic	80	0.258	0.438
High church attendance	110	0.355	0.479
Age (in years)	310	45.48	16.03
Married	141	0.455	0.498
At least some college education	173	0.571	0.495
Low income (HH income < $30K)	166	0.546	0.498

Male, White, Hispanic, Married, At least some college education, and Low income are dummy variables equal to one if the category is true. High church attendance = 1 if subject reports attending church at least once a week.

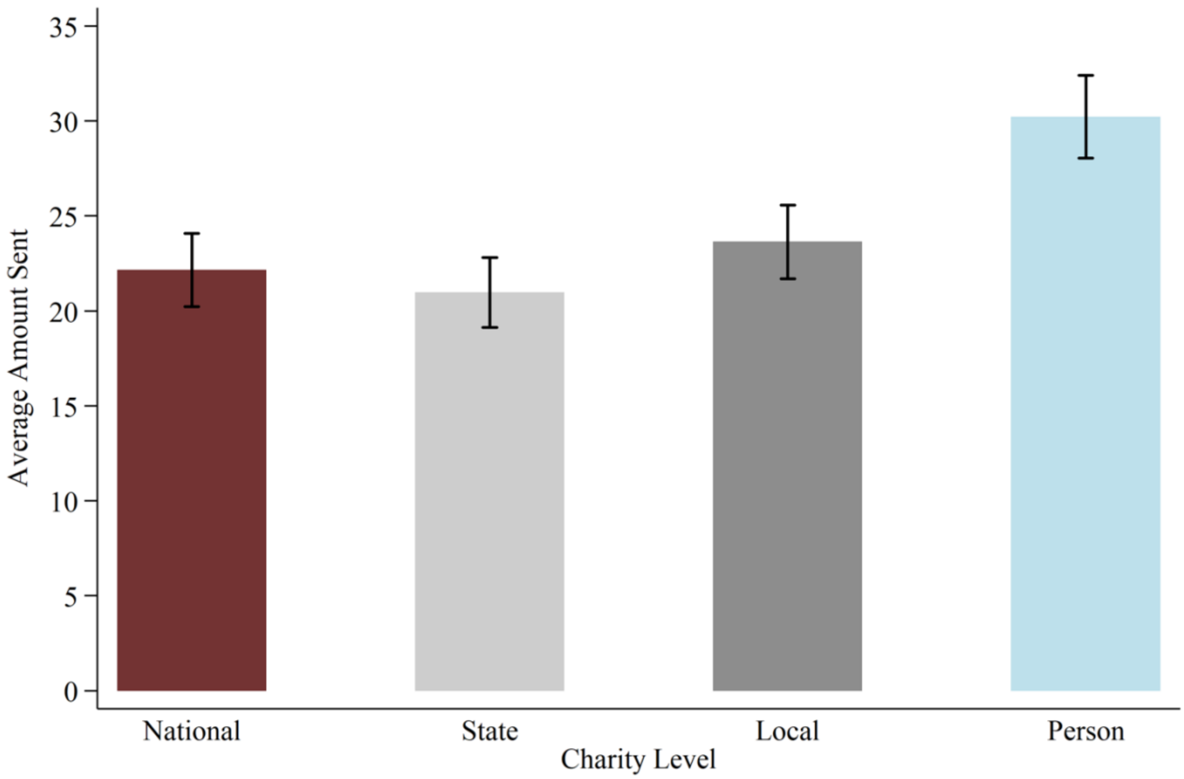
In addition to socio-demographics, subjects responded to survey questions assessing trust in different organizations and individuals. A selection of these questions was used to calculate two additive scales measuring trust in institutions and trust in people (Table 3). The "Trust in Institutions" index uses five items to capture subjects' underlying trust in institutions (Cronbach's alpha = 0.84). The "Trust in People" index uses three items to capture trust in people (Cronbach's alpha = 0.61). The questions used to calculate each index can be found in Appendix C. Subjects report a relatively high trust in people and, on average, are more trusting of people than institutions. We include these measures as covariate controls, reasoning that trust in institutions might be important for donation decisions that reach beyond the local level.

Table 3: Summary of Calculated Attitudinal Indices

Variable	Mean	Std. Dev.	Min	Max	No. Items	Cronbach's Alpha
Trust in Institutions	2.412	0.714	1	4	5	0.84
Trust in People	3.151	0.644	1	4	3	0.61

Figure 3 shows the average amount sent to each charity level. Table 4 in provides corresponding summary statistics. Panel A includes the average amount sent out of the $60 endowment, the probability of a subject sending a positive amount, and the average amount sent by donors (conditional on a positive donation). Panel B provides the same measures by characteristics with amounts pooled by subject – they reflect an average across all four decisions.

Figure 3: Average Giving, by Charity Level



Error bars represent 95% confidence intervals.

Table 4: Summary of Dictator Game Decisions

	Average Amount Sent	Probability of Donating	Conditional Average Amount Sent
Panel A: Comparative Dictator Game by Level			
National charity	22.17	0.871	25.45
State charity	20.98	0.871	24.09
Local charity	23.65	0.877	26.95
Person in town	30.23	0.919	32.88
Panel B: Comparative Dictator Game Demographics			
Male	23.99	0.866	27.70
Female	24.49	0.897	27.29
High church attendance	27.48	0.918	29.92
Low church attendance	22.49	0.866	25.96
College	23.50	0.855	27.50
No college	25.26	0.925	27.32
HH income < $30,000	22.56	0.883	25.57
HH income ≥ $30,000	26.38	0.888	29.71
Panel C: How many people sent their highest/lowest amount to each level?			
	Number sending highest amount	Number sending lowest amount	
National charity	28	35	
State charity	20	67	
Local charity	32	83	
Person	134	29	
Panel D: % Choosing Each Level in Selected Dictator Game			
National charity	16.77		
State charity	8.39		
Local charity	23.23		
Person in town	51.61		

N=310 for Panels A, B, and D. In Panel C, subjects were omitted if they sent the same amount to every level. High church attendance = 1 if subject reports attending church at least once a week. College = 1 if subject reports having at least some college education.

In Figure3, we see that subjects gave \$20–\$30 on average, or 33–50 percent of their \$60 endowments. Average giving was highest for the individual, and the lowest for the state-level charity. Even though gifts to the local charity clearly benefit local victims, subjects are even more likely to donate, and to give more, to a specific local victim. Subjects allocate more to national than state (*t*-test, $p = 0.06$, Wilcoxon signed rank test, $p = 0.02$) and more to local than national (*t*-test, $p = 0.04$, Wilcoxon, $p = 0.16$) or state (*t*-test, $p = 0.00$, Wilcoxon, $p = 0.00$). Subjects allocate a statistically and economically significant amount (\$6.58–\$9.25) more to the individual than to any other level (*t*-test, $p = 0.00$, Wilcoxon, $p = 0.00$ for all levels). We also see a higher probability of giving to the individual recipient. In particular, 91.94% of the subjects allocated a non-zero amount to the individual—4.2%–4.8% more than any other level (*t*-test, $p = 0.00$, Wilcoxon, $p = 0.00$ for all levels).

Turning to demographic differences in Panel B of Table 4, we see similar levels and likelihoods of giving by women and men. Likewise, there is not a statistical difference in propensity to give or amount given between more and less religious people or people with higher or lower income. Subjects without any college education are seven percentage points more likely to give some positive amount than those with at least some college education (*t*-test, $p = 0.03$, Mann–Whitney, $p = 0.03$), give \$1.76 more on average (*t*-test, $p = 0.03$), and have significantly different giving distributions (Mann–Whitney $p = 0.00$).

Since each decision was made independently subjects could give the same amount to each level, making their max and min equivalent. We call these subjects consistent givers and cover a more detailed analysis of them in Section 4.3. Among those who discriminated in the amount they gave by treatment, 134 (29) subjects gave more (less) to the individual person than to any other target. There is a clear revealed preference for charity level by where subjects gave their personal max and min amounts (seen in Panel C of Table 4).

In the SDG, subjects indicated which of the four decisions they most preferred to implement. More than half of subjects (51.6%) chose the individual person target, which reveals a strong preference for an identifiable victim. Interestingly, the choices in the SDG mirror the pattern of giving in the CDG, with a U-shaped revealed preference curve across level distance: 16.8 selected the national charity, 8.4 percent the state, and 23.2 percent of subjects selected the local level charity decision. However, not every difference is statistically significant and there is likely level-specific heterogeneous behavior, so a more thorough statistical treatment is necessary.

4. Regression Results

The aggregate results show that people differentiate among charities. We now focus on the relationship between subjects' characteristics and their donation behavior. First, we use the comparative dictator game (CDG) subject-level panel to analyze the full sample. Second, we break the regressions apart by CDG level to investigate level-specific heterogeneous behavior among characteristics. Third, we discuss the consistent givers who gave the same amount to each recipient level. Last, we examine what subjects choose in the SDG and offer explanations for this behavior.

4.1. Comparative Dictator Game: Pooled Sample

Donating behavior was restricted to be between \$0 and \$60, so we use a Tobit model to account for subjects who might have preferred to give less than \$0 or more than \$60 in the absence of this restriction. We use four different specifications to evaluate the relationship between these characteristics and giving:

$$G_i = \alpha + \boldsymbol{L\gamma} + \varepsilon_i \qquad (1)$$

$$G_i = \alpha + \boldsymbol{L\gamma} + \boldsymbol{D\beta} + \varepsilon_i \qquad (2)$$

$$G_i = \alpha + \boldsymbol{L\gamma} + \boldsymbol{I\delta} + \varepsilon_i \qquad (3)$$

$$G_i = \alpha + \boldsymbol{L\gamma} + \boldsymbol{D\beta} + \boldsymbol{I\delta} + \varepsilon_i \qquad (4)$$

where $\boldsymbol{L}$ is a vector of level indicator controls (national, local, and person); $\boldsymbol{D}$ is a vector of demographic variables (age, male, high church attendance, college, and low income); and $\boldsymbol{I}$ is a vector of our constructed trust indices (institutions and people). ε_i is the subject-specific error term. $\boldsymbol{L}$ will capture any level-specific differences in giving, independent of demographics, with state as the control variable. Based on Figure 3 and Panel A of Table 4, we expect the coefficients on national, local, and person to be positive and significant.

There is a large, existing literature on individual differences in altruistic behavior in the lab, typically measured by variations on dictator games. Gender has been extensively studied: in standard dictator games, where the recipient is an anonymous individual, women give more than men (Eckel and Grossman, 1998; Engel , 2011), although the gender difference may reverse if the relative price of giving is sufficiently low (Andreoni and Vesterlund, 2001). In "real donation" experiments (Eckel and Grossman, 1996), women also tend to give more than men, though this difference may vary by context. Two papers survey studies of charitable giving across methodologies and summarize findings on many factors including gender, age, education, religiosity, etc. (Bekkers and Wiepking, 2011; 2012). Age, education, and income are consistently positively correlated with giving, but gender and religiosity show mixed results. From this literature, we predict age, education, and household income will have a consistent, significant, positive effect on giving. Since the literature is not entirely clear on how our other demographic covariates correlate with dictator game decisions, especially across each of our three non-human recipients (charities), we use the summary information in Panel B of Table 4 to guide our predictions: we expect gender and our measures of religiosity to have no effect. Though race is commonly and reasonably included as a control variable, our sample is predominantly white and therefore does not have enough variation to detect any racial effects. Including race in the analysis did not meaningfully change our results in any way.

The results for specifications (1) – (4) are displayed in Table 5. The state-level charity is omitted for comparison. Consistent with the identifiable victim literature and Hypothesis 1, the coefficient on the person in town is significant and large in all specifications: subjects give considerably more to the person than to other levels (e.g., subjects give on average \$11.50 more than to the state organization). We conclude from this that when an individual is included in the consideration set the relative impact of a donation becomes more salient than its geographic reach, in comparison to giving to other (organization) recipients.

Hypothesis 2 posits that the organizations will be considered differently than the individual recipient and, following Li *et al.* (2011), we will observe donation magnitude to correlate with organizations' reach. We do not find consistent support for this hypothesis in Table 5. Subjects tend to give more to the national (\$1.58) and local (\$3.34) charities than to the state charity. Importantly, our full model (4) shows subjects giving a statistically significant amount more to every level than to state.

Table 5: Tobit Results for Comparative Dictator Game

Dependent Variable: Amount Sent	(1)	(2)	(3)	(4)
National charity	1.371 †	1.566 *	1.389 †	1.581 *
	(0.807)	(0.770)	(0.811)	(0.777)
Local charity	3.104 **	3.317 **	3.124 **	3.340 **
	(0.925)	(0.883)	(0.934)	(0.893)
Person in town	11.53 **	11.66 **	11.57 **	11.71 **
	(1.224)	(1.230)	(1.228)	(1.235)
Age (in years)		0.252 **		0.240 **
		(0.0737)		(0.0728)
Male		−1.046		−0.858
		(2.253)		(2.205)
High church attendance		4.011 †		2.990
		(2.339)		(2.271)
College		−4.192 †		−4.165 †
		(2.225)		(2.242)
Low income		−2.866		−1.564
		(2.385)		(2.356)
Trust in institutions			1.722	2.579 †
			(1.512)	(1.547)
Trust in people			6.959 **	5.203 **
			(1.823)	(1.725)
Constant	19.97 **	11.37 *	−6.198	−11.19
	(1.165)	(4.638)	(6.251)	(7.762)
σ	22.01 **	21.18 **	21.54 **	20.87 **
	(1.053)	(1.011)	(0.999)	(0.990)
Observations	1,240	1,200	1,236	1,196
Number of subjects	310	300	309	299

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

This causes a U-shaped giving curve across geographic level of operation. The relationship between ‘National’ and ‘State’ is consistent with Li *et al.* (2011) but the relationship between ‘State’ and ‘Local’ is exactly the opposite. There are two potential explanations for this difference: sample composition and consideration set. Our sample consists of adults aged 18–86 (mean of 45) instead of students, which (under Hypothesis 3b) we believe affects beliefs about the effectiveness of organizations operating at each level that informs charitable behavior. We test this more formally below. Another potential explanation is that we have added an individual to the subjects' consideration set. Though each decision was made independently, simply adding the individual could affect how subjects consider giving to the other charities, possibly by shifting some internal reference point. We do not claim this as fact but offer it as conjecture, as our experiment is not designed to test how an additional recipient in the consideration set affects reference points.

There is markedly little evidence of significant demographic effects on giving across these specifications. Consistent with the literature and Hypothesis 3b, age is consistently positive and significant ($p < 0.01$) and economically meaningful: 10 additional years of age corresponds to a \$2.40–\$2.50 increase in giving. Considering our sample spans ages 18–84 there is room for considerable differences in giving behavior.[62] Men give slightly less than women, but the difference is insignificant. Church attendance (religiosity) has a weak positive relationship to giving behavior here, which is possibly driven by giving to the Salvation Army (a religiously-affiliated charity). People earning less than \$30,000 a year give less than those earning more but not in a statistically meaningful way. Having at least some college education is negatively correlated with the amount given. Though this relationship is not statistically significant ($p < 0.1$), the sign is counterintuitive: education is typically positively correlated with giving.

Columns 3 and 4 include the trust survey measures, which are a preliminary test of Hypothesis 3a. Trust in institutions does not have a significant effect on giving. Trust in people, however, has an economically and statistically significant relationship with giving across both

[62] Results for second and third degree polynomials for age were insignificant. We concluded that a linear specification was most appropriate.

specifications: when accounting for other factors, an additional point increase in trusting people corresponds to approximately a \$5 increase in sending ($p < 0.01$). We do not draw any definitive conclusions on Hypothesis 3a from these results, because we suspect that these indices will have a clearer relationship with giving when analysis is disaggregated. Still, it is surprising that "Trust in People" has an effect on the pooled data because it is likely to be isolated to lower levels (local and person). This suggests that people who score high on this index either always give large amounts (to all levels) or the effect is so strong in the lower levels that it is not washed out by pooling the data. Results below suggest that the former explanation is correct.

As discussed above, subjects gave approximately \$10 more to the individual than any other level. This supports the importance of impact over reach when giving to an identifiable victim. Beyond this, however, rejecting Hypothesis 2 means impact and reach are related to each other. Subjects likely respond to some mixture of these two factors heterogeneously at each level, so we now turn to the disaggregated analysis.

4.2. Comparative Dictator Game: Disaggregated Analysis

We retain similar Tobit models as in 4.1, but restrict each specification by level (j) which necessarily means we no longer include level controls:

$$G_{ij} = \alpha + \boldsymbol{D}_j \boldsymbol{\beta}_j + \varepsilon_{ij} \tag{5}$$

$$G_{ij} = \alpha + \boldsymbol{I}_j \boldsymbol{\delta}_j + \varepsilon_{ij} \tag{6}$$

$$G_{ij} = \alpha + \boldsymbol{D}_j \boldsymbol{\beta}_j + \boldsymbol{I}_j \boldsymbol{\delta}_j + \varepsilon_{ij} \tag{7}$$

where $\boldsymbol{D}_j$ and $\boldsymbol{I}_j$ are the demographics and trust indices vectors defined as above for each level j and ε_{ij} is the subject-level specific error term. The results for equation (7) are displayed in Table

6. Results for specifications (5) and (6) are not meaningfully different from (7) and are available in Table B-1.

Table 6: Tobit Results for Comparative Dictator Game, by Charity Level

Amount sent to:	National	State	Local	Person
Age (in years)	0.263 **	0.202*	0.306**	0.182 †
	(0.0870)	(0.0792)	(0.0802)	(0.100)
Male	−3.350	-2.874	1.719	1.345
	(2.471)	(2.246)	(2.440)	(3.066)
High church attendance	1.349	0.339	3.177	7.558 *
	(2.608)	(2.366)	(2.565)	(3.141)
College	−5.082 *	-4.707*	-3.286	−3.616
	(2.533)	(2.299)	(2.439)	(3.019)
Low income	0.474	-0.0584	-0.803	−6.375 *
	(2.629)	(2.370)	(2.575)	(3.144)
Trust in institutions	5.265 **	3.500*	1.409	−0.06
	(1.843)	(1.614)	(1.753)	(2.082)
Trust in people	2.306	5.383**	6.697**	6.432 *
	(2.109)	(1.773)	(1.949)	(2.547)
Constant	−6.895	-10.85	-14.80+	5.719
	(8.718)	(7.866)	(8.659)	(10.65)
σ	20.19 **	18.59**	19.73**	24.29 **
	(1.190)	(1.092)	(1.142)	(1.410)
Number of subjects	299	299	299	299

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

As with the aggregate analysis, age has a persistent, significant, positive relationship with giving, further confirming Hypothesis 3b. Across all levels, an additional 10 years corresponds to sending between \$2.02–\$3.06 more. When controlling for all factors this age effect is strongest with the local-level charity.

There is also level-specific heterogeneity in other demographic characteristics. Consistent with the findings from Section 4.1, the coefficients on gender, church attendance, and income are not statistically distinguishable from zero at the national, state, or local level. This changes when people make allocation decisions with a person. Subjects with high church attendance give $7.56 more ($p < 0.05$), on average, to a person than subjects with low church attendance, when including all relevant covariates. This further supports our conclusion that measuring organization-level preferences are not confused with *organization* preferences in our experiment (i.e. religious subjects do not display a preference for the Salvation Army *because* it is a religious organization).

Subjects who make less than $30,000 a year give $6.38 less ($p < 0.05$), on average, than subjects with a higher income. This implies that the identifiable victim effect is stronger for people with higher church attendance and higher incomes. Likewise, this implies that, if reach is a dimension on which subjects make charitable decisions, it is uncorrelated with most demographics or, at least, they do not systematically move together (e.g. men do not systematically value the reach of national over state charities more than women). The coefficient on college education is negative and significant ($p < 0.05$) at the national and state level, meaning that subjects with more education gave approximately $5 ($4.70) less to the national (state) level charity. This implies there is some relationship between education and beliefs about the efficacy of higher-level charities. Since education is almost always an endogenous choice, we don’t make a causal claim.

The trust indices offer additional insights. We observe that an additional point on the institutional trust index corresponds to sending approximately $5 more to the national charity ($p < 0.01$). This means that an increased trust in institutions is meaningfully expressed in giving behavior, supporting Hypothesis 3a that subjects hold underlying beliefs about the efficiency of different charity-levels. Further supporting Hypothesis 3a, institutional trust carries over to affect giving to the state charity (\$3.50, p <0.05). Consistent with intuition, the magnitude of the institutional trust effect monotonically diminishes as the recipient becomes 'closer' to the subject where 'trust in people' instead takes over as the operating behavioral mechanism. The institutional trust index is uncorrelated with political party affiliation (covariance = 0.0687) or political ideology (covariance = 0.0533), and the effect documented in Table 5 is unchanged by the inclusion of party and ideology controls.

The coefficient on the index for trusting in people is similarly consistent with intuition and Hypothesis 3a. An increased trust in people (by one point on our index) corresponds to a \$5.38, \$6.70, and \$6.43 increase in giving to the state charity ($p < 0.01$), local charity ($p < 0.01$), and person ($p < 0.05$), respectively, when controlling for other demographic characteristics. As noted in Section 4.1, subjects who score higher on the 'people trust' measurement likely give more in general, though it is apparently limited to 'lower level' recipients. We would expect a trust in people to most strongly affect giving to a person, but interestingly it does not. This is likely because other factors take over at the person level (religiosity or income). Overall, we find strong support for Hypothesis 3a between our two trust indices with a slight modification—beliefs about the trustworthiness of institutions and people map into donative behavior in a meaningful way.

4.3. Consistent Givers

One challenge to interpreting our results from the CDG above and the SDG below are subjects whose revealed preferences exhibit indifference between recipient levels. The allocation decision at each level was made independently, but this does not preclude subjects from giving the same amount to each recipient. Ninety-six subjects (30.97% of the sample) were *consistent givers*:

they allocated the same amount to each recipient. Table 7 shows a summary of the consistent givers by demographics.

Table 7: Summary of Varying and Consistent Givers' Characteristics

	Frequency (%)	Age (average)	Male	High Church	College	Low Income
Varying	214 (69.03%)	46.05	0.43	0.39	0.57	0.52
Consistent	96 (30.97%)	44.22	0.39	0.28	0.56	0.59

Table 7 shows that restricting our results to only varying givers (subjects who did not send the same amount to all recipients) would make our sample slightly older, more male, more religious, and lower income. There is no statistically significant relationship between demographic characteristics and the likelihood of being a consistent giver, with the exception of religiosity: frequent church attendees are less likely to give the same amount to each recipient (Table B-3).

Consistent people most frequently chose to evenly divide the $60 endowment (30.21%) and ended up at the extremes of $0 (keep everything) and $60 (send everything) approximately 15.63% and 14.58% of the time, respectively. A detailed description of the consistent givers' donation distribution is in Table B-2. Basically, we see no reason to believe that including consistent givers biases our results; omitting them leaves us with less statistical power.

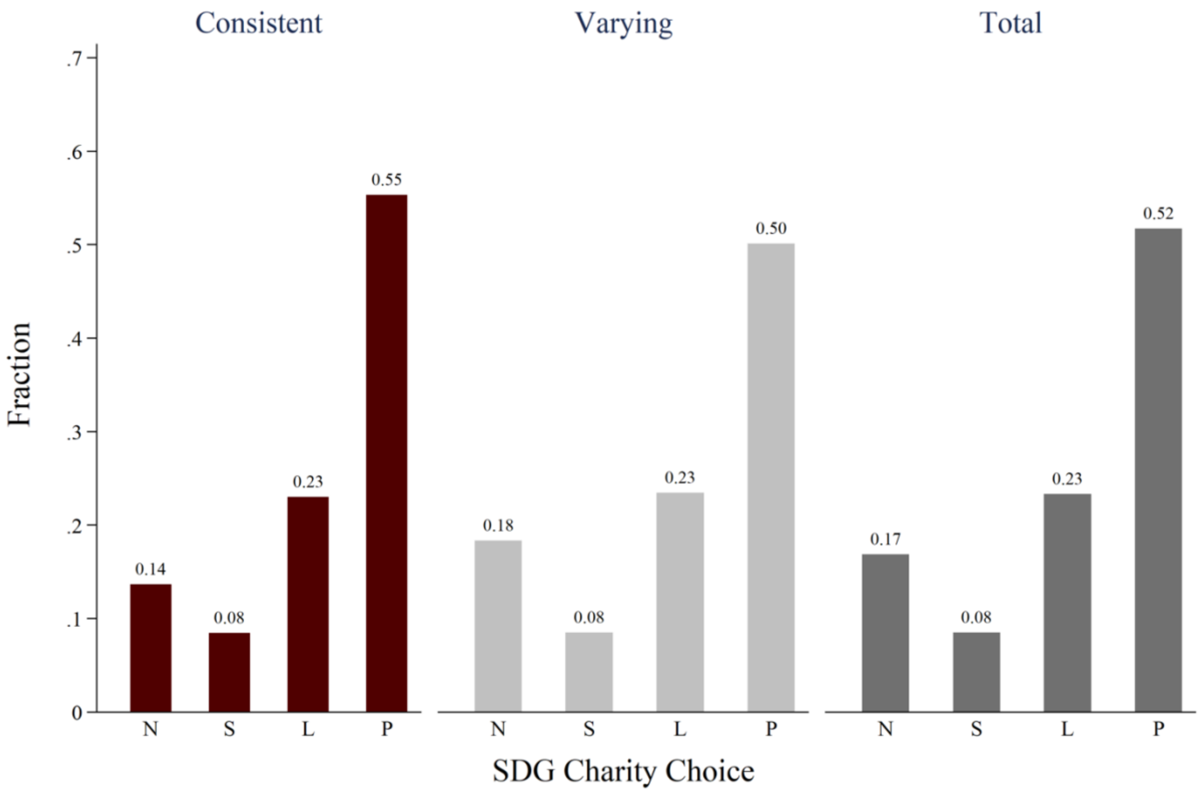
4.4. Selected Dictator Game

We now turn to the selected dictator game (SDG), the second task, where subjects chose one recipient out of the four levels from the CDG. If the SDG was selected for payment, subjects received the allocation for their chosen level from the CDG, with the remainder going to the selected organization. Subjects were unaware of the SDG when making allocation decisions in the

CDG. The SDG is a form of revealed preference. However, it has three implications. First, it can indicate which charity the subject most prefers, independent of their allocation choice. Second, it could reveal an income-enhancing preference in which subjects chose the charity to which they gave the least (thereby maximizing what they earned if the task were selected for payment). Finally, it could reveal the subject's desire to maximize their contribution to a charity in which the subject chose the charity to which they gave the most. Disentangling this from the first implication is difficult except for those subjects who always gave the same amount to each charity. As stated in Hypothesis 4 and consistent with Candelo *et al.* (2019), we expect subjects to be income-enhancing and choose the charity to which they gave the least in the CDG.

Figure 4 shows what proportion of subjects chose each level, as well as the distributions for consistent and varying givers. Consistent with giving patterns observed in Section 4.1, the majority of subjects prefer the individual person to be the recipient followed by local, national, and then state charities. Revealed preference theory tells us that consistent givers are indifferent between each of the levels. If that were true, we should see uniformity in the first distribution. Not only is the consistent givers' distribution not uniform, but it is remarkably similar to the varying givers' and total distributions. This implies that consistent givers are not truly indifferent between levels and are not so different from varying givers but have a similar behavioral response mechanism (weighing impact and reach).

Figure 4: Consistent and Varying Givers in the Selected Dictator Game



Results presented for level – National (N), State (S), Local (L), and individual person (P) – over consistent and varying givers and the full sample. Consistent givers sent the same amount to all four levels in the Comparative Dictator Game. Varying givers sent a different amount to at least one charity in the Comparative Dictator Game.

Following the results from Section 4.2, there are plausibly heterogeneous preferences for SDG choice by demographic characteristics. For example, if people who attend church more give more to a person recipient, we can hypothesize that they will also be more likely to choose that level in the SDG. We test these choice and demographic relationships using an ordered logit model. We are interested in estimating the probability of choosing each level given some control variables, or $P(C = k \mid \boldsymbol{D}, \boldsymbol{A}, \boldsymbol{I}), \forall k = 1, 2, 3, 4$, where $\boldsymbol{D}$ and $\boldsymbol{I}$ are defined as above, $\boldsymbol{A}$ is a vector containing the amount each subject sent to each level, and C is defined as

$$C = \begin{cases} 1 & if\ C^* \leq \mu_1 \\ 2 & if\ \mu_1 < C^* \leq \mu_2 \\ 3 & if\ \mu_2 < C^* \leq \mu_3 \\ 4 & if\ C^* > \mu_3 \end{cases} \tag{8}$$

We calculate this using the latent variable models

$$C^* = \boldsymbol{D\beta} + \boldsymbol{A}\lambda + \xi \tag{9}$$

$$C^* = \boldsymbol{D\beta} + \boldsymbol{A}\lambda + \boldsymbol{I\delta} + \xi \tag{10}$$

An ordered logit model is particularly well-suited for this estimation because our charities' levels retain a natural ordering (where 1 = national, 2 = state, 3 = local, and 4 = individual). Estimating this model gives us the predicted probability that subject *i* selects charity *j* from their decisions in the CDG, conditional on their characteristics (i.e., age, gender, church attendance, income, education), their trust indices, and the amounts they sent to each level. The results are displayed in Table 8.

We find little evidence of demographics influencing charity choice in the SDG. The only variable that is significant at conventional levels is age: There is a negative relationship between age and the level chosen ($p < 0.05$), meaning that older persons are less likely to select local organizations.

We now turn to the analysis testing Hypothesis 4. In their CDG study, Candelo *et al.* (2019) observed this purely selfish behavior. They argue that subjects must compete internally between financial self-interest and the desire to feel charitable by giving some amount away, and show that in their case, financial self-interest ultimately overpowered subjects' altruism. We do not observe this: the coefficients on the donations to each recipient are small and statistically insignificant, and uncorrelated with their choice in the SDG.

Table 8: Ordered Logit Results for Selected Dictator Game

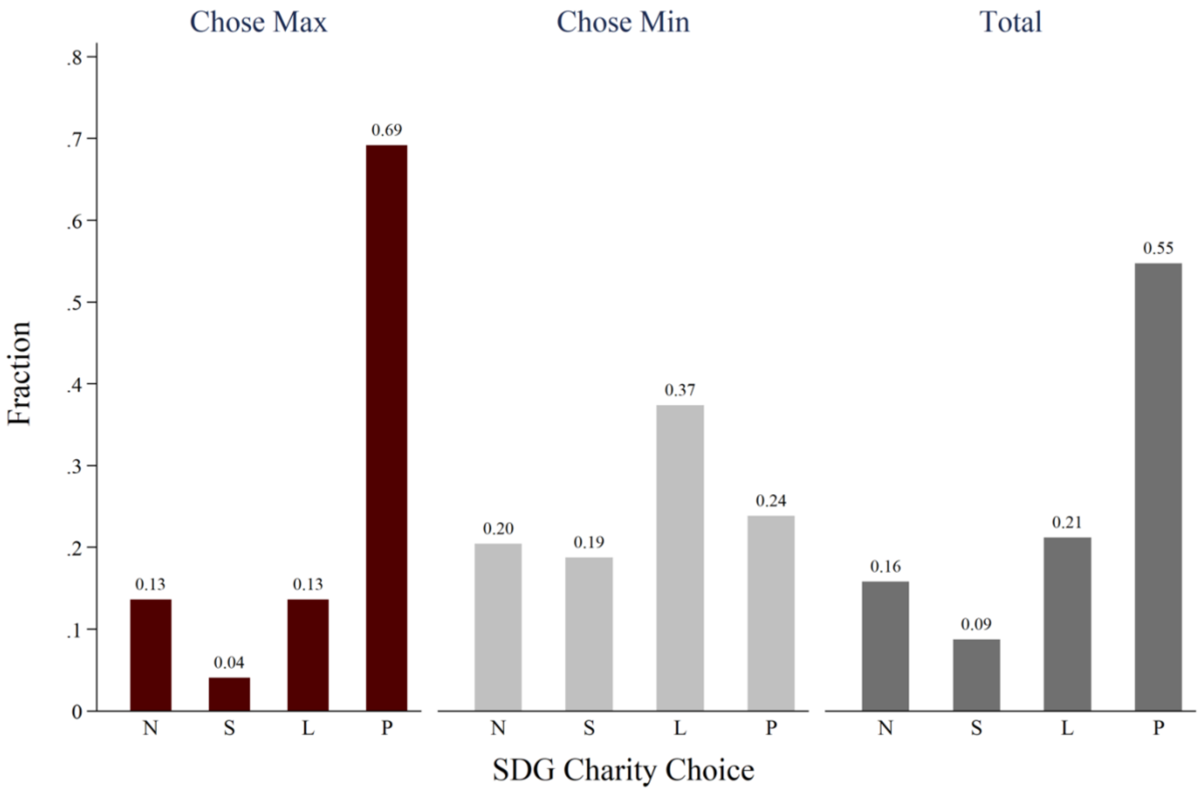
Dependent Variable: Charity Level Chosen	(9)		(10)	
Age	−0.0143 †	(0.0076)	−0.0157 *	(0.0077)
Male	0.295	(0.234)	0.265	(0.235)
High church attendance	0.247	(0.254)	0.256	(0.257)
College	−0.360	(0.257)	−0.388	(0.261)
Low income	−0.334	(0.273)	−0.321	(0.276)
Amount sent to national	−0.0180 †	(0.0103)	−0.0172 †	(0.0103)
Amount sent to state	−0.00979	(0.0133)	−0.00959	(0.0135)
Amount sent to local	0.0133	(0.0126)	0.0133	(0.0129)
Amount sent to person	0.0159 †	(0.0087)	0.0156 †	(0.0088)
Trust in institutions			−0.135	(0.191)
Trust in people			0.0394	(0.223)
Cutoff 1	−2.338 **	(0.522)	−2.603 **	(0.836)
Cutoff 2	−1.781 **	(0.507)	−2.045 *	(0.823)
Cutoff 3	−0.715	(0.490)	−0.974	(0.809)
Observations	300		299	

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

We examine this more closely in Tables 9 and Figure 5. We restrict our analysis here to varying givers only, since the minimum and maximum charities are equivalent for consistent givers. Table 9 is a tabulation of how many subjects chose each level in the SDG and breaks this down by those who chose the charity where they sent the least (min charity) and the most (max charity). We define a subject's min (max) charity as the recipient to which they gave less (greater) than or equal to the next lowest (highest) amount sent to all other recipients by that subject. Figure 5 shows this information as a percentage of the total within each panel. For example, 23.73% (69.05%) of the subjects who chose their min (max) charity in the SDG selected the 'person' level.

Table B-4 shows probit results for the probability of choosing the min (columns 1–2) and max (columns 3–4) charity for each of our main covariates (demographics and indices).

Figure 5: Choosing the Maximum and Minimum in the Selected Dictator Game



Results presented for level – National (N), State (S), Local (L), and individual person (P) – over subjects that chose their max or min charity and the full sample. Chose Max (Min) denotes that a subject chose the level in the Selected Dictator Game to which they sent the most (least) in the Comparative Dictator Game.

Table 9: Summary of Selected Dictator Game Choices

	Total	National	State	Local	Person
Full sample	310	52	26	72	160
Varying givers	214	39	18	50	107
Chose min	59	12	11	22	14
Chose max	126	17	5	17	87
Chose other	29	10	2	11	6

Consistent givers are omitted from lines 2-5 because their minimum and maximum are equivalent.

Table 9 shows that substantially more people chose their max charity (126) in the SDG than their min charity (59). This further supports the rejection of our Hypothesis 4.

Additional analysis (see columns 1 and 2 of Table B-4) show that no socio-demographic variables are correlated with the probability of choosing one's min charity in the SDG. The coefficient on the people trust index is negative and statistically significant ($p < 0.05$): An additional point of trust on the index corresponds to a 36.2% decrease in the probability of choosing the min charity. This is unsurprising given the strong, positive relationship between this index and the amount sent (as described in Table 6). Those with higher trust in people are likely much more generous donors. They are not so altruistic, however, as to choose the max charity as shown in column 4. The coefficient on the people trust index is positive but is not significant at conventional levels ($p < 0.1$). Interestingly, men are much more likely than women (54%, $p < 0.01$) to choose their max charity in the SDG. This is surprising considering there were no gender differences in the amounts given across levels. Furthermore, the literature typically posits women as behaving more altruistically than men while we find the opposite here.

5. Discussion and Conclusion

We use a comparative dictator game and selected dictator game to explore how subjects differentiate between charities at different levels (national, state, local, individual) that have similar missions. Our study is conducted using a sample of adults, and our experiments are coupled with a survey collecting rich set of demographic and attitudinal information, which allows us to test for demographic and attitudinal correlates of charitable giving. To our knowledge, we are the first to use this experimental design with adults and the first to include an anonymous individual in the consideration set alongside different charity-levels with a similar mission.

We anticipated that donors might consider the breadth of the reach of the charitable organization, as well as the impact of their own donation in making their allocations. We hypothesized that impact would be most salient when considering an identifiable person, so giving would be highest at that level. We find support for this hypothesis, with subjects giving roughly \$6.50–\$9.50 more to the individual than any other level. We then propose that subjects consider organizations differently than an individual because the impact of their donation is less clear. We find only some support for our hypothesis that giving monotonically increases with the level, finding instead a U-shaped giving curve: giving to national and local charities was higher than state charities. We also find heterogeneous effects on giving by age and indices that measure trust in institutions and people. This confirms that giving behavior is at least partially determined by beliefs about the relative effectiveness of aid at each level, which varies across subjects. In addition, we find that college educated donors are more likely to give to a national charity, while church goers are more likely to provide charity at a local or individual level.

Finally, when given the opportunity to select which of their dictator decisions to be implemented, we are able to see whether people pursue a strategy of maximizing their own earnings by choosing their smallest donation, or whether they select the target to which they donated the most, reflecting their preferences for the altruistic action. Importantly, donors are not indifferent across charities, choosing the local victim more than half the time. This is true even for those who donate the same amount to all four charitable recipients. While these people should be indifferent between the four recipients, as revealed by their donation amounts, they are not, as revealed in their greater likelihood of selecting the anonymous individual recipient. Drawing from a similar, previous study, we hypothesized that donors would ultimately act in their own financial self-interest, choosing the charity to which they gave the least in the CDG. We reject this hypothesis, finding that subjects primarily select the organization to which they gave the most, revealing a stronger preference for altruism than selfishness in this environment.

For fundraisers, our research has three implications. First, we further confirm the importance of highlighting individual recipients whenever possible. Donors value the relative impact of their donation and this impact is clearest when the recipient is an identified individual (even if the person is anonymous). While this is not a novel idea to current philanthropic fundraising practices, we believe there is a second important takeaway for organizations operating at several levels. If soliciting donations for a menu of operating levels within an organization, including an individual recipient on the list may change behavior. Lastly, if the organization operates at many geographic levels (local, state, national), we recommend including all of them on the menu – separate from an identifiable individual – for potential donors to consider so that they may self-select into giving to whichever level they prefer based on their own beliefs and values.

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CHAPTER VI

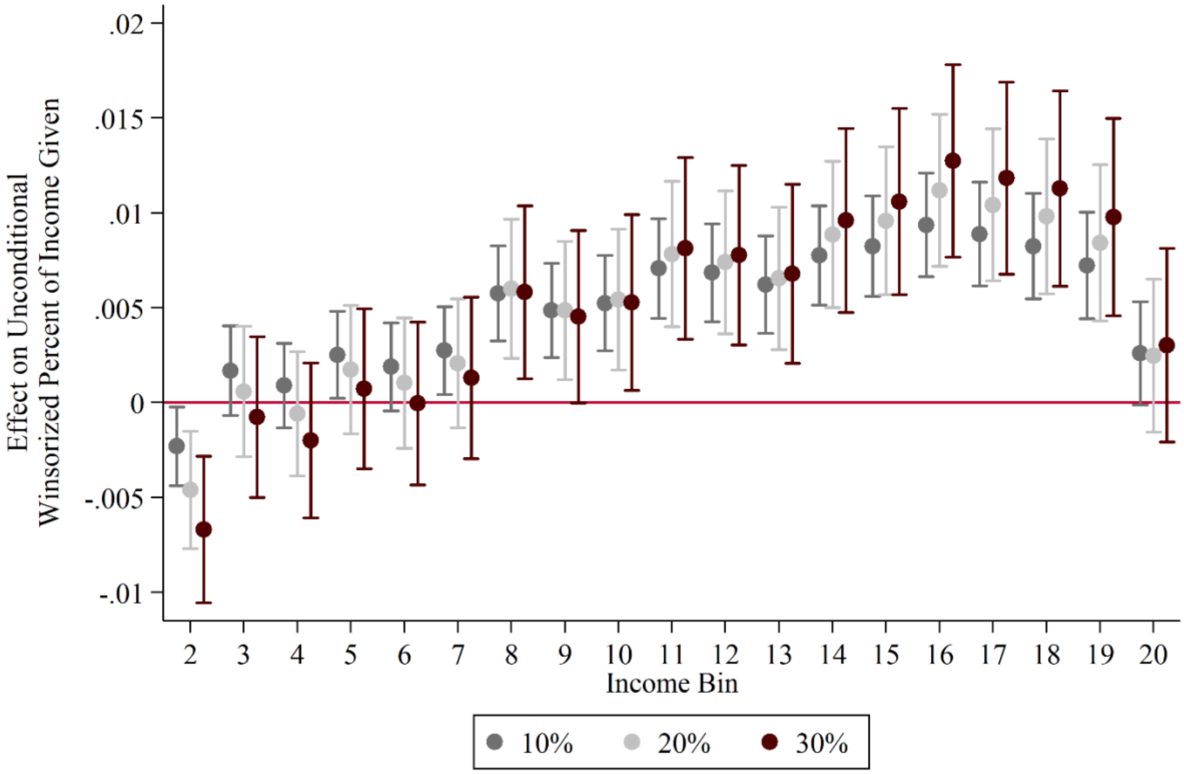
SUMMARY

Charitable giving is a fundamental household financial decision – even when giving isn't planned, nearly everyone will be solicited for donations at some point in their life either by a friend, family member, neighbor, or stranger volunteering for a nonprofit. Moreover, charitable giving is a significant part of the economy – both as a percent of GDP and as an employer – that affects the lives of all Americans. Being such a fundamental decision, it is crucial that we understand how households think about donations to better inform philanthropists and policy makers.

We discussed here four different behavioral facets of charitable giving: responses to changes in resources (income and wealth), responses to changes in real tax policy, responses to changes in hypothetical policy, and how beliefs about people and institutions mediate donative behavior in disaster relief. Each chapter expands the wealth of knowledge that exists in the field of economics and altruistic behavior and opens many additional research questions to further advance the field.

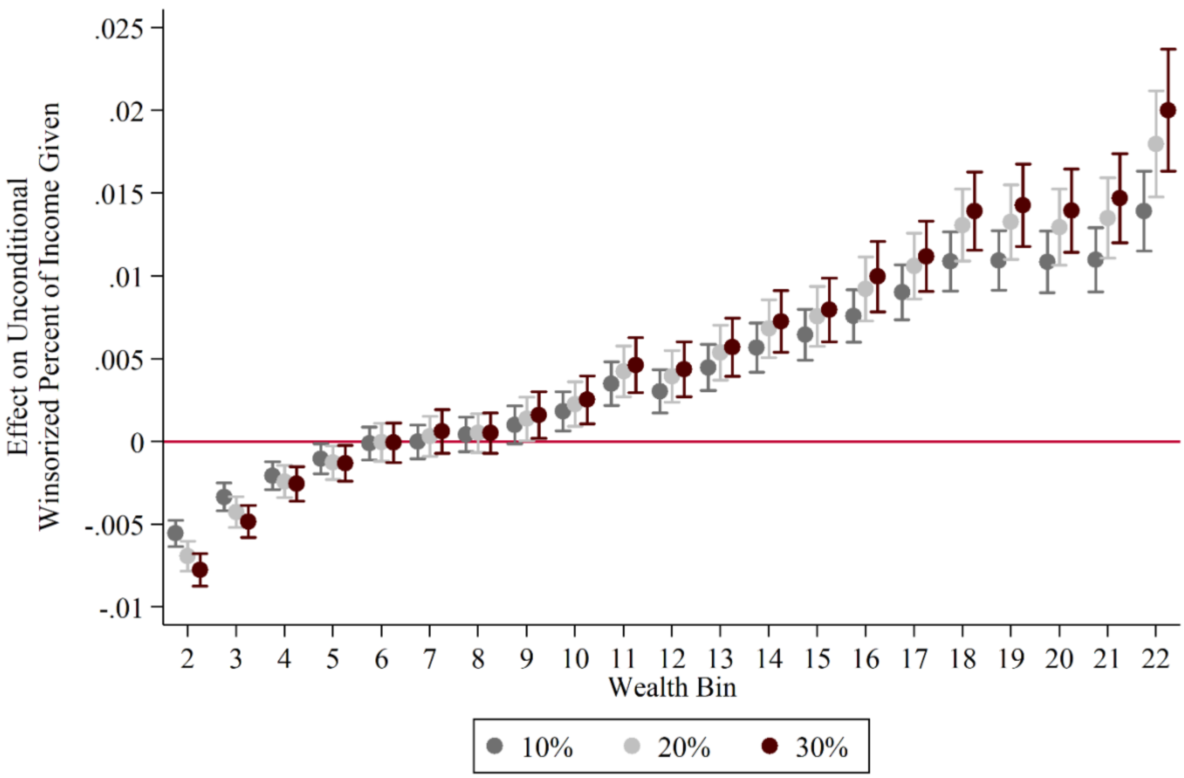
APPENDIX A

Figure A-1: OLS, Unconditional Winsorized Percent of Giving, by Income



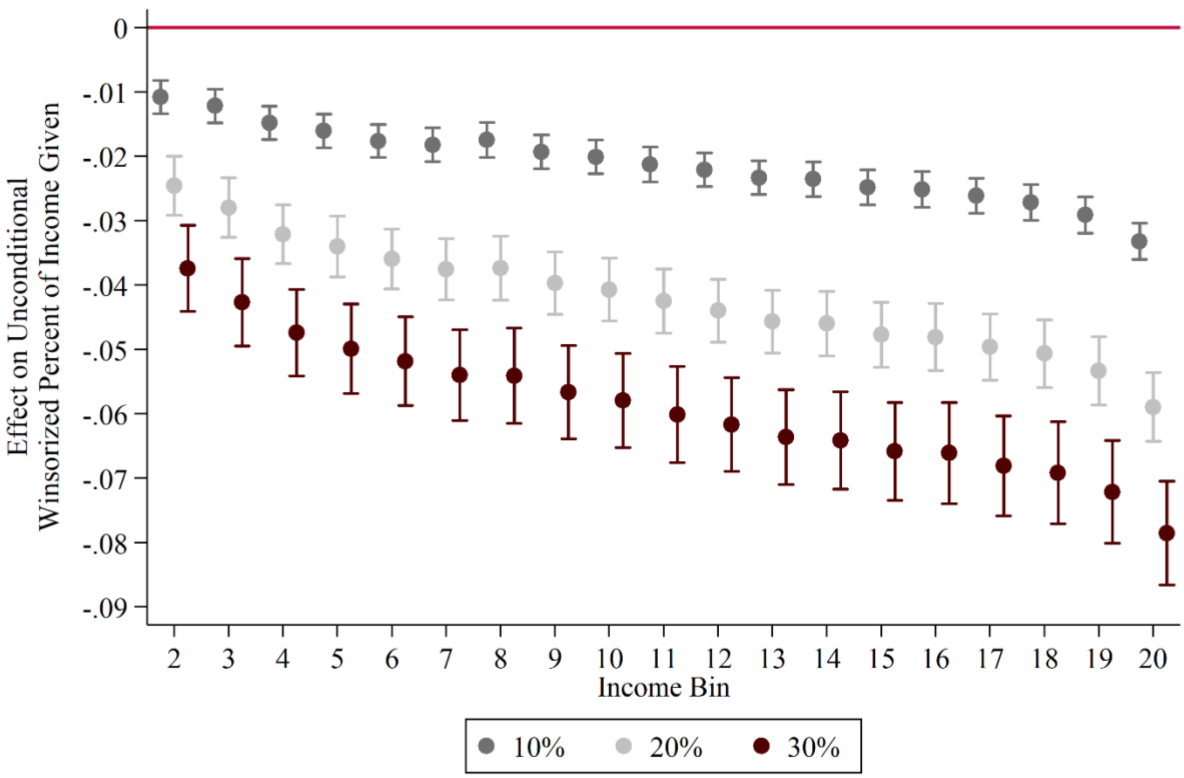
Notes: This figure displays the coefficients for each income bin from OLS regressions for three levels of winsorizing: 10%, 20%, 30%. Estimates combine the extensive and intensive margins. Winsorizing caps the maximum possible percent of income given for a household at 10%, 20%, or 30%. Households giving a larger proportion of their income are assigned a value equal to the maximum. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Household characteristics described in Section 3.2 are included. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figure A-2: OLS, Unconditional Winsorized Percent of Giving, by Wealth



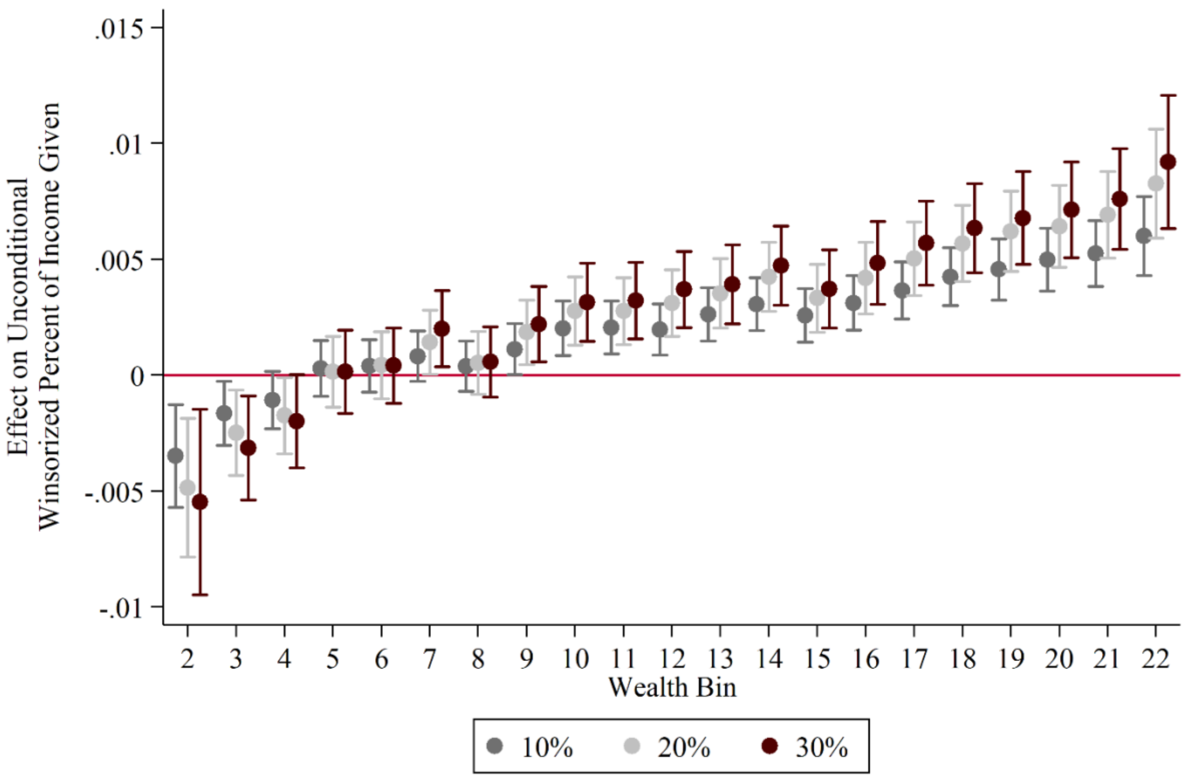
Notes: This figure displays the coefficients for each wealth bin from OLS regressions for three levels of winsorizing: 10%, 20%, 30%. Estimates combine the extensive and intensive margins. Winsorizing caps the maximum possible percent of income given for a household at 10%, 20%, or 30%. Households giving a larger proportion of their income are assigned a value equal to the maximum. All specifications include wealth bin and year indicators; the lowest wealth bin (negative wealth) is omitted for comparison. Household characteristics described in Section 3.2 are included. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figure A-3: Fixed Effects, Unconditional Winsorized Percent of Giving, by Income



Notes: This figure displays the coefficients for each income bin from fixed effects regressions for three levels of winsorizing: 10%, 20%, 30%. Estimates combine the extensive and intensive margins. Winsorizing caps the maximum possible percent of income given for a household at either 10%, 20%, or 30%. Households giving a larger proportion of their income are assigned a value equal to the maximum. All specifications include income bin and year indicators; the lowest income bin is omitted for comparison. Time-varying household characteristics described in Section 3.2 are included. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

Figure A-4: Fixed Effects, Unconditional Winsorized Percent of Giving, by Wealth



Notes: This figure displays the coefficients for each wealth bin from fixed effects regressions for three levels of winsorizing: 10%, 20%, 30%. Estimates combine the extensive and intensive margins. Winsorizing caps the maximum possible percent of income given for a household at either 10%, 20%, or 30%. Households giving a larger proportion of their income are assigned a value equal to the maximum. All specifications include wealth bin and year indicators; the lowest wealth bin (negative wealth) is omitted for comparison. Time-varying household characteristics described in Section 3.2 are included. Error bars represent the 95% confidence interval. Robust standard errors are clustered at the household level.

APPENDIX B

Table B-1: Additional Tobit Results for Comparative Dictator Game, by Level

Amount Sent to:	National		State		Local		Person	
Age (in years)	0.242**		0.211**		0.332**		0.214*	
	(0.086)		(0.079)		(0.083)		(0.099)	
Male	−3.802		−3.036		1.63		1.296	
	(2.508)		(2.323)		(2.478)		(3.083)	
High church attendance	2.49		1.579		4.17		8.22*	
	(2.683)		(2.422)		(2.63)		(3.181)	
College	−5.665*		−4.865*		−3.028		−3.214	
	(2.52)		(2.285)		(2.395)		(3.043)	
Low income	−0.157		−1.44		−2.437		−7.941*	
	(2.646)		(2.407)		(2.601)		(3.106)	
Government		4.739**		3.228*		0.548		−1.951
		(1.721)		(1.577)		(1.78)		(2.071)
People		2.959		6.181**		8.601**		10.26*
		(2.044)		(1.847)		(2.151)		(2.636)
Constant	14.45**	0.544	14.65**	−7.250	8.977†	−5.392	24.81**	4.2
	(5.069)	(6.88)	(4.721)	(6.404)	(5.066)	(7.282)	(5.993)	(8.68)
σ	20.53**	20.71**	19.06**	19.2**	20.11**	20.76**	24.57**	25.3**
	(1.205)	(1.191)	(1.122)	(1.094)	(1.177)	(1.163)	(1.408)	(1.448)
Number of subjects	300	309	300	309	300	309	300	309

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

Table B-2: Distribution of Amounts Sent by Consistent Givers

Amount Sent	Frequency	% of Consistent	% of National	% of State	% of Local	% of Person
$0	15	15.63	37.50	37.50	39.47	60.00
$1	1	1.04	16.67	16.67	25.00	100.00
$5	3	3.13	17.65	23.08	37.50	42.86
$6	2	2.08	40.00	33.33	28.57	66.67
$10	16	16.67	31.37	27.59	34.78	43.24
$20	11	11.46	21.57	23.40	20.75	26.19
$30	29	30.21	40.85	42.03	38.16	39.19
$35	1	1.04	33.33	20.00	33.33	100.00
$40	3	3.13	13.04	18.75	13.04	13.64
$50	1	1.04	14.29	11.11	12.50	7.69
$60	14	14.58	58.33	73.68	50.00	22.58

Table B-3: Demographic Differences between Consistent and Varying Givers

Dependent Variable: *Probability of Being A Consistent Giver*	OLS	Probit
Age	−0.000578	−0.00144
	(0.000863)	(0.00252)
Male	−0.0387	−0.112
	(0.0274)	(0.0782)
High church attendance	−0.109 **	−0.318 **
	(0.0284)	(0.0850)
College	0.0129	0.0383
	(0.0286)	(0.0807)
Low income	0.0289	0.0865
	(0.0287)	(0.0820)
Constant	0.375 **	−0.328 *
	(0.0533)	(0.151)
Observations	1200	1200
R^2	0.018	

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$.

Table B-4: Probit Results for Choosing Min and Max in Selected Dictator Game

Subject Chose Their Personal:	Min		Max	
	(1)	(2)	(3)	(4)
Age	−0.0103 †	−0.00794	0.00345	0.00126
	(0.00616)	(0.00647)	(0.00583)	(0.00615)
Male	−0.311	−0.323	0.540 **	0.542 **
	(0.198)	(0.204)	(0.187)	(0.192)
High church attendance	−0.195	−0.164	0.250	0.233
	(0.206)	(0.208)	(0.195)	(0.199)
College	−0.133	−0.0636	0.186	0.133
	(0.202)	(0.210)	(0.195)	(0.202)
Low income	0.388 †	0.303	−0.249	−0.180
	(0.209)	(0.215)	(0.195)	(0.199)
Government		0.0623		−0.0973
		(0.147)		(0.137)
People		−0.362 *		0.277 †
		(0.155)		(0.151)
Constant	−0.106	0.752	−0.194	−0.723
	(0.379)	(0.645)	(0.359)	(0.609)
Observations	205	205	205	205

Robust standard errors in parentheses: ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$. Analysis restricted to varying givers because consistent givers have no relative minimum or maximum amount.

APPENDIX C

C-1: Excerpt from Instructions at the Beginning of the Experiment

We are going to ask you to make some decisions and answer some questions. In the first part of this you will make some decisions to determine how much additional money you will receive. After all the decisions, you will answer some survey questions on natural disasters and other things about you and your community. Keep in mind that there are no right-or-wrong answers. We are interested in YOUR opinions and the way YOU make decisions. Are there any questions so far?

C-2: Excerpt from Instructions at the Beginning of Task 5 (Comparative Dictator Game)

Example 1—Look at the first decision. In this decision you have $60 which you must allocate between yourself and the recipient. Here the recipient is the American Red Cross Disaster Relief fund.

Now I am going to give you some information about the American Red Cross Disaster Relief Fund:

The American Red Cross Disaster Relief fund is a nonprofit charity that focuses on providing aid to disaster victims nationwide. It meets people's immediate emergency disaster caused needs for shelter, food and health services. In this box, you will write how much of the $60 you would like to allocate to the American Red Cross Disaster Relief Fund. Suppose you want to allocate $42. This means you will keep $18, the rest of the $60 you were given initially, for yourself. Notice, these amounts must add up to $60.

Example 2—Look at the second decision. In this decision you have $60 which you must allocate between yourself and the recipient. Here the recipient is the United Way of Texas.

Now I am going to give you some information about the United Way of Texas:

The United Way of Texas is a nonprofit charity dedicated to meeting the needs of people across the state. It enables health and human services to get back in operation after a disaster. In this box, you will write how much of the $60 you would like to allocate to the United Way of Texas. Suppose you want to allocate $6. This means you will keep $54, the rest of the $60 you were given initially, for yourself. Notice, these amounts must add up to $60.

Example 3—Look at the Third decision. In this decision you have $60 which you must allocate between yourself and the recipient. Here the recipient is the local Salvation Army. Now I am going to give you some information about the local Salvation Army. The local Salvation Army is a nonprofit charity which focuses on providing clothing and food to disaster victims locally. In this box, you will write how much of the $60 you would like to allocate to the local Salvation Army. Suppose you want to allocate $0. This means you will keep all $60 for yourself. Notice, these amounts must add up to $60.

C-3: Excerpt from Instructions Describing the Payment Selection Process

To decide which task is going to be paid, we will pick an envelope out of this box. The envelopes look just like this example (grab example envelope). Inside the envelopes are cards with numbers on them. On this example card you can see a number sign (open example envelope to show card with number sign). The card that's drawn will be numbered 1, 2, 3, 4, 5, or 6. The number that is selected is the number of the task you will be paid for.

C-4: Questions Used to Calculate Demographic Variables

Church Attendance

"How often do you attend church services or church related meetings?"

1=More than once a week
2=Once a week
3=A couple of times a month
4=Once a month
5=Rarely
6=Never

High church attendance is a binary variable set to unity if a subject reported attending church at least once a week.

Education

"Please indicate your highest level of education:"

1= Less than 9th grade
2= Between 9th grade and 12th grade (no diploma)
3= High school graduate or GED
4= Some college (no diploma)
5= Graduated from college (Associate's degree, Bachelor's degree or above)
6= Advanced degree

College is a binary variable set to unity if a subject reported having any college education.

Household Income

"What was your household income, before taxes and other deductions, from all sources (for example, wages, child support, alimony, investments, government or social assistance, grants) for the last 12 months? Please give us your best guess if the exact figure is not known."

1=Less than $10,000
2=$10,000 to less than $20,000
3=$20,000 to less than $30,000

4=$30,000 to less than $40,000
5=$40,000 to less than $50,000
6=$50,000 to less than $60,000
7=$60,000 to less than $75,000
8=$75,000 to less than $100,000
9=$100,000 to less than $125,000
10=Greater than $125,000

Low income is a binary variable set to unity if subjects report a yearly household income of less than $30,000.

C-5: Questions Used to Calculate Attitudinal Indices

Subjects responded to the below questions with the following scale.
1=Trust completely
2=Trust somewhat
3=Do not trust very much
4=Do not trust at all

Institutions:

How much do you trust the following: City government
How much do you trust the following: State (Texas) government
How much do you trust the following: The Governor
How much do you trust the following: Federal government
How much do you trust the following: FEMA

People

How much do you trust the following: Your neighbors
How much do you trust the following: Your coworkers
How much do you trust the following: Fire department
Indices were rotated to be increasing in trust and scaled to be between 1 and 4.