Three Essays on the Economics of Charity

by

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For my grandmother, Pearl Hecht Karol, of blessed memory.

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[1]Data used in Chapter I were obtained from OpenSecrets (`www.opensecrets.org`), formed by a merger of the Center for Responsive Politics and the National Institute on Money in Politics in 2021.

[2]Additional data used in Chapter I were obtained from the Wesleyan Media Project, a collaboration between Wesleyan University, Bowdoin College, and Washington State University, and includes media tracking data from Kantar/Campaign Media Analysis Group in Washington, D.C. The Wesleyan Media Project was sponsored in 2012-2018 by grants from The John S. and James L. Knight Foundation, and in 2012-2014 by grants from The John D. and Catherine T. MacArthur Foundation. The opinions expressed in this article are those of the author and do not necessarily reflect the views of the Wesleyan Media Project, Knight Foundation, MacArthur Foundation or any of its affiliates.

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ABSTRACT

This dissertation studies how charities' receipts and expenses respond to developments in the communities they serve. Chapter I studies the relationship between political contributions and charities' private donations and fundraising expenses. Chapter II studies how food aid charities respond to increasing food insecurity. Chapter III studies the effect of the coronavirus pandemic on the charitable sector.

Chapter I asks how political giving affects the finances of the average charity. This paper matches Form 990 data on charities' finances to Federal Election Commission and National Institute for Money in Politics data on political contributions made in the geographic area where the charity fundraises, during its fiscal year. A 10% increase in political contributions costs the average charity 0.79% of its private charitable contributions, implying that one dollar of political contributions crowds out nearly $3 in private charity. However, the majority of this crowd-out is attributable to changes in the charity's fundraising strategy. Subsequent analysis explores different channels through which political contributions may motivate the charity to adjust its fundraising. For most charities, political contributions reduce the return to charitable fundraising. One key exception is the human services sector. At these charities, the return to fundraising is unaffected by political contributions; however, they still lose private contributions. When paired with a model of optimal charitable fundraising in the presence of political contributions, these results imply that human services charities' production functions depend directly on the realization of the political state.

Chapter II investigates how donors to food assistance charities respond to exogenous changes in recipients' unmet needs. When food insecurity rises by one percentage point, the average food assistance charity increases fundraising by 0.9%. Without this response, private contributions would have fallen by at least 0.2%. These results are consistent with a model in which economic inequality simultaneously raises the donor's marginal benefit of giving and reduces their awareness of the recipient's circumstances. Charitable fundraising plays a key role in maintaining the charity's

revenues at a time when they are most needed.

Chapter III, coauthored with Jennifer Mayo, studies the effects of the coronavirus pandemic on the U.S. nonprofit sector. Using a difference-in-differences framework, we leverage variation in the timing of charities' fiscal years, finding that government intervention helped keep charities afloat during the pandemic. On average, government grants rose by $975,000, while private contributions fell by $380,000. Despite the net increase in their contributions, charities exposed to the pandemic lost employees and made fewer program expenditures than non-exposed charities. However, charities which had Paycheck Protection Program loans approved during the first year of the pandemic fared better than eligible charities without approved PPP loans.

CHAPTER I

Taking from Charity? Political Contributions and the Market for Charitable Funds

1.1 Introduction

A public good can be provided in one of two ways: either it can be provided privately, by charity, or it can be provided by the government. If a private citizen wishes to use their own resources to shape public good provision, they can try to exert influence over one or both of these channels, either by giving to charity or by supporting a politician's bid for office. Political and charitable contributions should therefore be considered as two alternative ways for donors to express their pro-social preferences.

A recent strand of the literature on altruism and public good provision has begun to characterize the relationship between these two categories of gifts. At present, the bulk of this young literature concludes that political donors view charitable and political giving as substitutes. However, it is not yet clear how much this substitution matters from the charity's perspective. Political contributions are quite rare in the United States, especially compared to charitable contributions. *Bouton et al.* (2022) are able to identify only 20.2 million unique political donors in the 2020 cycle, representing roughly 8% of the voting-age American population. By contrast, according to the most recent data from the Philanthropy Panel Study, just under half of American households report giving to charity (*Osili et al.* (2021)). In dollar terms, the aggregate amount of political giving is also small relative to the aggregate amount of charitable giving. During the 2019-2020 election cycle, federal elections were estimated to cost \$14.4 billion (*Evers-Hillstrom* (2021)), while aggregate private charitable giving in the US totaled \$466.2 billion in 2020 alone, or \$914.9 billion over the comparable two-year period (*Giving USA Foundation* (2019, 2021)). Even if political and charitable contributions are substitutes, can political giving actually make a difference to the charity's bottom line?

This paper finds that when political contributions rise, charities fundraise less, and receive fewer private contributions. The estimated elasticities imply that political contributions crowd out charitable giving at a rate of nearly three to one. This disproportionate impact occurs because political donors' behavior has spillover effects on other charitable donors' giving. In particular, political contributions reduce the net return to charitable fundraising. When a charity's potential donors give an additional \$1 million to politicians, the return to charitable fundraising falls by 23 cents on the dollar. As a result, charities cut back on fundraising expenses, which in turn reduces their receipts from both political and non-political donors to charity. While this mechanism is responsible for significant reductions in giving to the average charity, not all charities lose contributions for this reason. By allowing the measured elasticities to vary according to the charity's sector, this paper reveals that human services charities are quite different from organizations in other sectors. Human services organizations lose contributions because their donors perceive that these organizations' production functions depend on the realization of the political environment.

This paper also explores the role of ideology in determining the relationship between political and charitable giving. Ideology is measured by applying the algorithm developed in *Gentzkow and Shapiro* (2010) to bodies of text collected from charities' websites. The estimated elasticities of fundraising and private contributions to political contributions are significantly larger for left-leaning and ideologically moderate charities compared to apolitical charities. However, it is not possible to reject a null hypothesis that left-leaning, centrist, and right-leaning charities are equally sensitive to political contributions.

Why does the return to fundraising fall? Given the rarity of political donors in the population, it is unlikely that changes in the return to fundraising occur only because political donors may substitute between political and charitable giving. This paper explores the possibility that donations to politicians may affect charitable giving by non-political donors. Political contributions fund political campaigns, and these campaigns' expenditures are often made in order to persuade the electorate to vote. But if non-political donors view all pro-social actions, including gifts of time as well as gifts of money, as part of one "altruism budget" (*Gee and Meer* (2019)), then they may consider voting and donating to charity as alternative pro-social actions. By encouraging non-political donors to vote, political campaigns may unwittingly discourage charitable giving. This paper explores the extent to which exposure to one major category of campaign activity – political television advertising – may moderate the overall relationship between political and charitable giving. Its findings are consistent with substantial spillover effects between political and non-political donors to charity, which operate through this channel.

By focusing on charity-level responses to political giving, and characterizing heterogeneity in these responses by charity sector and ideology, this paper makes a major contribution to the emerging literature on the linkages between political and charitable contributions. It serves as a bridge between this growing literature and several more established bodies of work. These include the literature on the determinants of charitable fundraising, as well as the study of the extent to which donors' political ideology shapes their charitable behavior.

This paper is the first to explore the relationship between political and charitable giving using IRS Form 990 data. The primary dataset is formed by matching charity-level data from this federal information return to aggregated individual-level political contributions from the Federal Election Commission and the National Institute on Money in Politics. Furthermore, this paper employs text-based analysis of nonprofits' websites to produce a new measure of charity ideology. It should be of broad academic interest to all those who study nonprofits and the role of civil society in the political process, including but not limited to economists, political scientists, and sociologists.

The paper is organized as follows. Section 1.2 presents institutional context on charitable and political contributions in the United States, including asymmetries in their treatment by the legal and tax systems, and highlights the ways in which these asymmetries have shaped the existing literature. Section 1.3 outlines the empirical strategy used to estimate the relationship between political and charitable giving, implemented using data presented in Section 1.4. These estimates, presented in Section 1.5, allow for elasticities to vary according to the charity's sector and its ideology. Section 1.6 presents a model of optimal charitable fundraising in the presence of political contributions. Charities choose their fundraising expenses in order to maximize production of some charitable good, less any disutility associated with fundraising expenses. Charitable production depends on the ideological distance between the charity and the government. Political giving can affect the charity's choice of fundraising expenses in three ways. The insights derived from this model are used to structure the discussion of the mechanisms through which political giving may affect charitable fundraising, explored in Section 1.7. Section 1.8 concludes.

1.2 Charitable and Political Contributions in the United States

Charitable and political contributions are thought to serve some similar purposes in very distinct ways. These distinctions sometimes limit data availability in the United States, and these limitations shape all efforts to understand the relationship between the markets for political and charitable giving. Whereas prior work attempts to overcome these limitations by leveraging individual-level data in innovative ways, these efforts also suffer from their own limitations. By utilizing charity-level data, this paper can characterize the relationship between these two markets in a more complete manner. This section first provides an orientation to the institutional environment in which potential donors make political and charitable contributions, and then proceeds to outline the major contributions of the present work.

1.2.1 Institutional Background

While charitable and political contributions may be viewed as two alternative methods of influencing the set of public goods provided in a society, they are viewed and treated quite differently by the United States government and public. Political contributions are often regarded with suspicion due to their potential for corruption, while charitable contributions typically enjoy a more virtuous reputation. This asymmetric treatment extends to the organizations which solicit and receive these contributions, as well as to the transparency with which such contributions are reported.

As it turns out, for every possible motivation to make political contributions, there exists an exact analogy to the motives which drive charitable contributions. One major motive is the altruistic desire to shape public good provision (*Hersh and Schaffner* (2017)). Despite the lack of evidence, 75% of Americans persist in the belief that political donations change election outcomes (*Primo and Milyo* (2020)). This belief implies that making a campaign contribution to one's favorite candidate is an effective way of helping them win, and therefore a meaningful way of influencing public good provision. Of course, neither political nor charitable donations are motivated by altruism alone: there are many egoistic benefits associated with political giving. These include reputational benefits, the entertainment value derived from access to exclusive fundraising events, and any satisfaction privately derived from taking an action that supports one's own ideology. Some find that these benefits dominate donors' motivations, rendering political donations into "consumption goods" (*Ansolabehere et al.* (2003)) and casting their donors as "political hobbyists" (*Hersh* (2020)). However, in the parlance of the charity literature, these donors simply derive a "warm glow" from their political gifts, just as they do from charitable giving (*Andreoni* (1990)). Other motivations which drive political giving, such as a desire for access to elected officials (*Fouirnaies and Hall* (2014)), represent a convex combination of altruistic and egoistic motives. Due to the striking similarity in their underlying motives, it is possible that donors consider political contributions as part of their "altruism budget" (*Gee and Meer* (2019)).[1]

Although both types of contributions originate in the same set of motives, charitable and political contributions are viewed very differently by the American public.[2] Charity is viewed as a pro-social act, and a large body of experimental evidence attests to the reputational benefits of charity as a major driver of giving (*Ariely et al.* (2009); *Andreoni and Bernheim* (2009); *Bekkers and Wiepking* (2011); *Exley* (2018)). Many Americans believe that the well-off should give more to charity in order to use their wealth to do good (*Berman et al.* (2020)), though they are growing skeptical of the publicity which often accompanies large gifts (*Soskis* (2021)). By contrast, Americans tend to view wealthy donors' political contributions as a potential source of corruption, which may seek to subvert the "will of the people." Lack of transparency in political giving is viewed as a source of social harm (*Primo and Milyo* (2020)). However, it is not at all clear that political giving actually causes this supposed harm. Per *Dawood* (2015) and *Kalla and Broockman* (2018), the evidence that political contributions change electoral outcomes is quite sparse. However, it does not follow that political contributions are entirely wasteful. By changing the way political topics are framed and discussed, the campaigns funded by these contributions can have profound implications for voters'

[1]If donors include political contributions in their altruism budget, it may follow that they substitute between political and charitable giving if this altruism budget is fixed. *Reinstein* (2011) finds that, after controlling for donors' unobservable, time-invariant characteristics – such as innate altruism – that charitable donors do substitute between different categories of charitable expenditure.

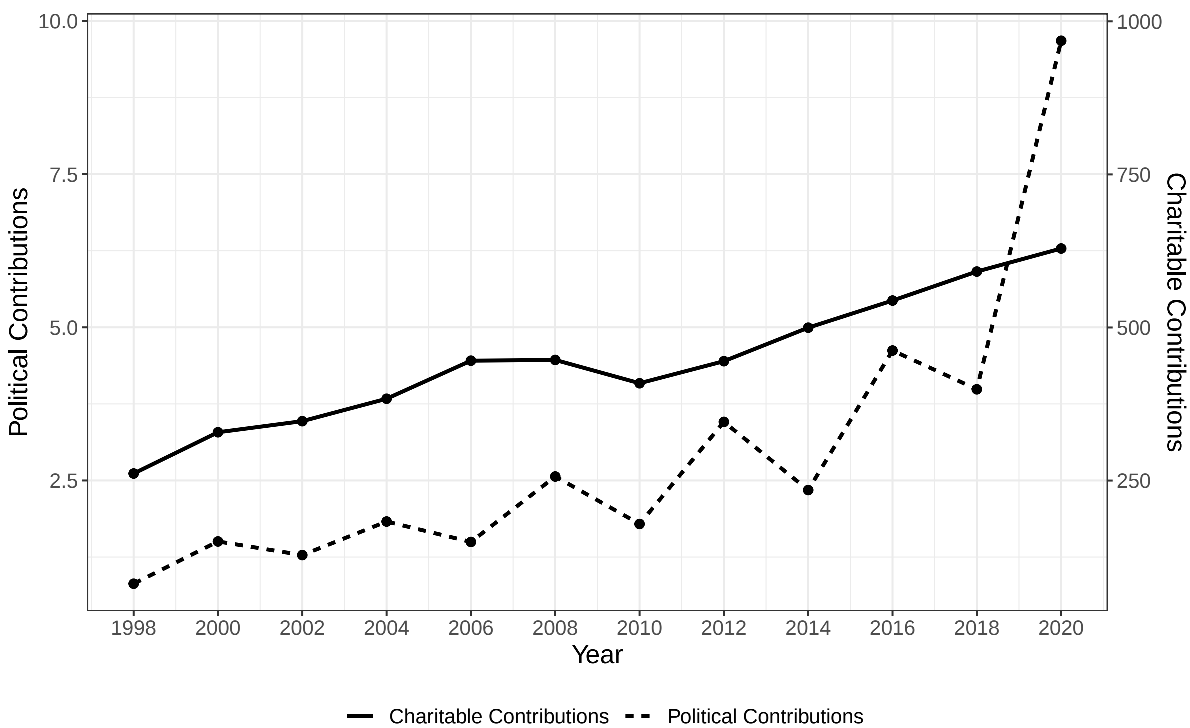
[2]For this reason, it is not obvious that donors think of political contributions as part of the altruism budget, despite their similarity to charitable contributions.

preferences, and therefore for social choice (*Branham and Wlezien* (2019)). Most estimates of these effects find that they are small in magnitude, in part because the effects of two opposing campaigns may tend to offset one another. Nevertheless, small aggregate effects may still be consequential for political campaigns.

How might political contributions be expected to affect elections? Political donations fund campaign advertising and other media-related expenses, which is both the largest single category of campaign spending and the main channel through which voters are exposed to the campaign (*Fowler et al.* (2016)). It follows that if political contributions affect electoral outcomes, these effects must operate through this advertising channel, which is thought to persuade or inform voters. Evidence shows that while political advertising can inform voters (*Fowler et al.* (2016)) and boost turnout (*Cancela and Geys* (2016)), the persuasive effects of campaign spending are low, both for voters (*Kalla and Broockman* (2018) and for legislators (*Reynolds and Hall* (2018)). The persuasive power of a campaign advertisement must overcome the power of political polarization in order to be effective; and in an environment of rising political polarization, this obstacle has grown more challenging over time. All in all, the evidence shows that political contributions are most productive when the electorate is not too polarized, and when they were previously under-informed about the candidates. For this reason, campaign advertising – and therefore campaign spending – is more likely to affect the outcome of a primary election than a general election (*Bonica* (2017)).

These asymmetric views of charitable and political giving may contribute to the disparities in the sizes of these markets: US charitable giving was estimated to be $466.23 billion in 2020 (*Giving USA Foundation* (2021)), compared to an estimated $14.4 billion spent on presidential and congressional elections in 2020 (*Evers-Hillstrom* (2021)). Figure 1.1 illustrates the discrepancy in size across these two types of gifts. Each point represents the aggregate amount of contributions by individuals over a two-year period. In the case of political contributions, the data presented refers to the aggregate amount of contributions made by all large individual donors. The volume of large individual donors' political contributions, while large, is roughly one-hundredth the size of the amount of charitable contributions made by individuals. However, its growth rate appears much higher than the growth rate of individuals' charitable contributions. Charitable giving is also far more prevalent than political giving: at least 50% of Americans report giving to charity (*Osili* *et al.* (2021)), compared to roughly 8% who give to politicians or political organizations (*Bouton et al.* (2022)).

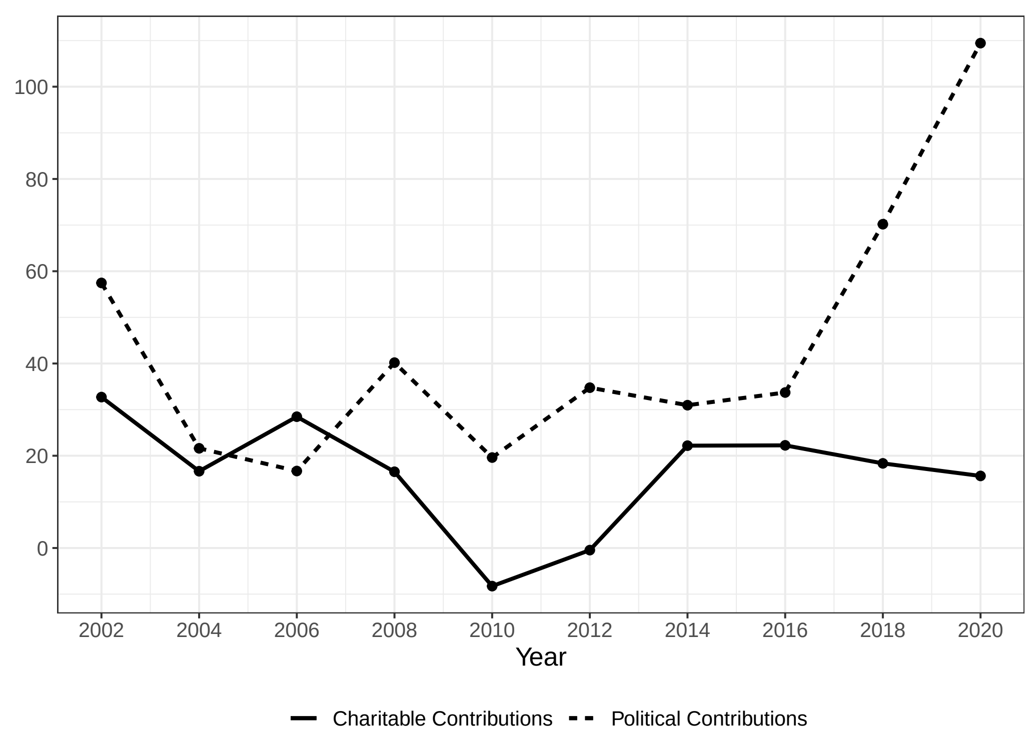
Asymmetric perceptions of these contributions drive their asymmetric treatment by the government. This asymmetry is present in the tax treatment of contributions, contribution limits, and transparency in reporting requirements. Charitable contributions to 501(c)3 nonprofits are deductible from income tax for those who itemize their deductions, up to a limit of 50% of adjusted gross income. Tax reforms may affect the price of charitable giving by changing the marginal tax rate, by encouraging or discouraging itemization, or by changing deductibility limits. However, the charitable deduction has been available since 1917. Prior to 1987, political contributions received favorable income tax treatment as well, though in a very different way. A 50% tax credit for political contributions was available up to a limit of $50 for individuals ($100 for married couples filing jointly), though this credit was repealed as part of the Tax Reform Act of 1986 and has not been reintroduced since.



Notes: Points represent sum of gifts made over the previous two years, in billions of current dollars. Data on individuals' charitable contributions from Giving USA. Data on large individual donors' political contributions from OpenSecrets.

Figure 1.1: Charitable and Political Giving by Individuals in the United States

While the government places no limits on charitable giving, it does regulate the amount of political contributions an individual is allowed to make. The modern era of campaign finance regulation can be traced back to the Federal Election Campaign Act of 1974, which followed closely on the heels of the Watergate scandal and gave birth to the Federal Election Commission (FEC). Two years later, in *Buckley v. Valeo*, the Supreme Court upheld the constitutionality of limits to individuals' political contributions, as well as disclosure requirements of these contributions, on the grounds that enforcing both limits and transparency prevent corruption or the appearance of corruption in federal elections. The ruling left a variety of loopholes in campaign finance law which enabled wealthy or highly motivated donors to circumvent both the limits and disclosure requirements, some of which were closed by the Bipartisan Campaign Reform Act of 2002. Campaign finance regulation attempts to balance these concerns about the appearance of corruption with First Amendment rights regarding freedom of speech, and in the years following the BCRA, several Supreme Court decisions altered this balance. One such regulation came in 2010, as *Citizens United v. FEC* overturned the ban on independent expenditures made by corporations, labor unions, and nonprofits. These expenditures have come to be known as "dark money."



Notes: Data on individuals' charitable contributions from Giving USA. Data on large individual donors' political contributions from OpenSecrets.

Figure 1.2: Four-Year Percentage Change in Donations, by Type

While some nonprofit organizations are permitted to make these expenditures, 501(c)3 nonprofits remain prohibited by the Internal Revenue Code from "directly or indirectly participating in, or intervening in, any political campaign on behalf of (or in opposition to) any candidate for elective public office" (*Internal Revenue Service* (2022b)). While charities are prohibited from participation in political campaigns, they are quite free to subscribe to any political ideology. Charities are often formed by political minorities to provide goods and services that cannot be produced by the government, because it is constrained by the democratic process (*Rose-Ackerman* (1997)). A sizable minority of charities are formed for the specific purposes of advocating for, and educating about, causes which may be advanced or thwarted by the implementation of various public policies. Charities may advocate for a policy, or encourage get-out-the-vote efforts, so long as they do not violate the IRS' prohibition on campaigning for or against a candidate for public office. Should an organization violate this prohibition, they may lose their tax-exempt status. In order to get around this prohibition, some 501(c)3 organizations choose to form related 501(c)4 nonprofits, which may make unlimited independent expenditures, though donations to these organizations are not tax-deductible.

Political contributions made by 501(c)4 nonprofits have been given the moniker of "dark money" because 501(c)4 advocacy organizations, like 501(c)3 public charities, do not have to disclose their donors. Donor privacy is considered to be a fundamental right, without which the government might restrain an individual's freedom of association. In a 2021 decision (*Americans for Prosperity Foundation v. Bonta, Attorney General of California*), the Supreme Court upheld protections against disclosure of charitable donations on these grounds. No such right to privacy exists for political contributions: as discussed above, the strict disclosure requirements which apply to political contributions are considered essential to avoid the appearance of corruption in legislation. As a result, data availability is quite different for political and charitable contributions in the United States. For the most part, individual political donations are observable by the researcher, while individuals' charitable contributions can only be observed under certain circumstances. These asymmetries in data availability have profoundly impacted the study of the relationship between political and charitable contributions in the United States.

1.2.2 Contribution to the Literature

This paper contributes to three strands of the literature on charitable giving. It is primarily situated in the emerging literature characterizing the relationship between political and charitable giving. Within this literature, it is the first to use IRS Form 990 data to quantify this relationship. Due to its use of charity-level data for a broad cross-section of US charities, it further innovates by documenting heterogeneity in this relationship across charities. It is also the first to emphasize the impact of political contributions on the charity's choice of fundraising strategy. While this relationship is implicit in several previous theoretical models of charitable fundraising, this paper contributes to the literature on determinants of fundraising by explicitly and empirically documenting this relationship. Finally, this paper serves to connect this developing body of knowledge with prior work measuring the impact of political ideology on charitable giving.

This paper contributes primarily to the growing body of knowledge documenting the effects of the political process on charity. Politics can motivate both individual and corporate charitable giving for a variety of reasons. At one extreme, it may motivate giving out of a strategic desire to influence politicians (*Bertrand et al.* (2020)); at the other, it can alter the social context in a way that encourages individuals to express their pro-sociality through contributions (*Hungerman et al.* (2018)). Within this body of scholarly work, the study of the linkage between political and charitable contributions notes that the same pro-social motivations may underlie both types of gifts. For this reason, it has focused primarily on determining whether donors view these two goods as substitutes or complements. The literature has not yet reached a consensus on the nature of donors' preferences. Using survey data from the Consumer Expenditure Survey between 1990 and 2001, *Yörük* (2015) finds that political and charitable donations are complements. While the Consumer Expenditure Survey appears to be the only survey in the United States to ask about both political and charitable donations, it suffers from a variety of limitations, which are inherited by Yörük's pioneering work. Notably, the Consumer Expenditure Survey is a cross-sectional survey, which prevents the econometrician from controlling for time-invariant donor characteristics, such as attitudes towards altruism. Like all surveys, it suffers from recall bias. Finally, given the time period covered by these data and the timing of efforts towards campaign finance reform in the United

States, it is likely that the relationship between political and charitable giving has changed since 2001. Using more recent data, *Petrova et al.* (2020) attempt to overcome some of these limitations by matching aggregated individual-level data on political contributions from the Federal Election Commission to two charities' donor databases. The charities in question are the American Red Cross and Catholic Charities, both of which are very large and relatively non-partisan organizations, providing disaster relief and human services, respectively. Using identifying variation from political advertisements and the incidence of natural disasters, Petrova and coauthors estimate that these donors consider political and charitable contributions to be substitutes. However, the authors' focus on these two particular charities limits the external validity of these estimates. Nevertheless, the main result – that donors substitute between these two types of giving – is echoed by *Cagé and Guillot* (2022). These authors leverage identifying variation from a 2018 wealth tax reform in France, which created a positive shock to the price of charitable giving but not to political giving. While the French context differs substantially from the United States both in its political organization and the scope of its philanthropic sector, these authors also conclude that political and charitable giving are substitutes.

Previous research in this area has thus far maintained an implicit assumption that observed patterns of giving represent only a donor's own preferences, as opposed to the equilibrium outcome of a market for charitable giving. This market has two sides: donors represent the supply side, while charities make up the demand side. As the number of elections varies over the course of a four-year election cycle, so do the number of competitors for donors' contributions, and therefore the probability that a given charitable donor also provides financial support to some political candidate. A rational charity will be aware of these fluctuations, and may change its fundraising strategy accordingly. Whereas previous work abstracts away from these demand-side effects and their consequences, this paper will be the first to consider how political contributions affect charitable fundraising, in addition to aggregate receipts by the charity. This is accomplished through the use of charity-level data, which allows for heterogeneity in the impact of political giving on charities' fundraising and contributions received along several important dimensions. This emphasis on the effect of political giving on charitable fundraising constitutes a contribution to the literature on the determinants of charitable fundraising (*Rose-Ackerman* (1982); *Steinberg* (1986); *Andreoni* (1998);

Yi (2010); *Andreoni and Payne* (2011); *Name-Correa and Yildirim* (2013)). While several of these papers acknowledge that a charity's ideology may affect its fundraising strategy or its popularity with donors, this work will build on this intuition to illustrate the connection between charities' fundraising strategies and the election cycle.

Thus far, papers documenting the relationship between political and charitable giving have paid scant attention to the role of donors' political ideology in shaping patterns of substitutability or complementarity. In the case of *Yörük* (2015), this area cannot be explored due to data limitations: the Consumer Expenditure Survey asked respondents about the amount of their political contributions, but not the identity of the recipient or the political leanings of the respondent. By contrast, *Petrova et al.* (2020) do implement a test for partisan differences in contributions. The authors find that natural disasters affect political contributions to Republicans and Democrats in approximately the same way. This result may follow from the narrow focus on contributions made for one specific cause. After all, political donors are ideologically extreme relative to the general population (*Hill and Huber* (2017)), and the subset of political donors whose giving is impacted by information shocks regarding foreign aid may not be representative of the overall response. Further research is needed to reach a definitive conclusion regarding the partisan nature of the relationship between political and charitable giving.

This paper will therefore be among the first in this literature to forge a link with previous work on the effect of donors' political ideology on charitable giving.[3] Several foundational models of charitable fundraising acknowledge that charities may subscribe to some particular ideology, and that donors choose which charities to support based in part on the match between their own ideology and the position of the charity (*Weisbrod* (1977); *Rose-Ackerman* (1982)). The body of literature seeking to rationalize the existence of the private charitable sector does not always explicitly acknowledge that charities can serve ideological functions. However, many models in this area depict voluntary provision as the result of dissatisfaction with public provision (*James* (1986); *Rose-Ackerman* (1996)). This view is distinct from familiar notions of crowd-out (*Warr* (1982); *Bergstrom et al.* (1986)), which abstract away from political considerations in determining

[3] *Bertrand et al.* (2020) discusses the way corporate contributions to charities or foundations may be used as strategic forms of lobbying politicians, but these donations appear to be motivated primarily by influence-seeking by corporations, rather than individuals' partisan preferences.

the quality of the public goods on offer. In this perspective, a substantial part of the social value of the charity comes from its ability to offer goods and services which would not be provided by the government, because government provision requires a degree of political consensus by which the charity is not bound. This theory is supported by results from *Karlan and List* (2007), in which the authors send fundraising appeals for the Sierra Club, a left-leaning and politically-oriented charity, to individuals in all 50 states. The authors find that fundraising appeals containing matching grants were far more effective in generating contributions from donors in "red" states compared to donors in "blue" states. This result is particularly remarkable given that all donations generated by this study went to support a left-leaning charity, suggesting that the individual donors who responded to the fundraising appeal may hold minority political opinions within their state. This study represents some of the highest-quality evidence documenting the effect of ideology on charitable giving. Overall, this literature is remarkably mixed: some studies find support for the *Brooks* (2007) hypothesis that conservatives are more generous than liberals owing to their political ideology (*Paarlberg et al.* (2019)), while others find that this relationship is driven largely or entirely by partisan differences in religious engagement (*Vaidyanathan et al.* (2011); *Forbes and Zampelli* (2013); *Yen and Zampelli* (2014)). More recent work has provided experimental evidence that self-identified conservatives may be more generous than self-identified liberals (*Balliet et al.* (2021), *Brewer et al.* (2022)). These studies ascribe partisan differences in generosity to differential parochialism: conservatives are more likely to support local charities, while liberals are more likely to support national or international charities.

The present work makes two contributions to the literature on partisan differences in charitable giving. First, this paper will use text analysis to produce a measure of ideology for a broad range of charities. This metric, based on *Gentzkow and Shapiro* (2010), is produced in a procedurally similar manner to the one employed by *Hungerman et al.* (2018) to describe the partisan lean of Catholic parishes. This paper fills a crucial gap in this literature by characterizing the ideology of a wider selection of charitable organizations. Second, it will use this measure to document whether, and by how much, the effect of political contributions on charitable fundraising and receipts varies by the ideological orientation of the charity. The largest differences in these effects should be found at charities with particularly partisan missions.

1.3 Empirical Strategy

This section describes the strategy for estimating average elasticities of charities' fundraising expenses and contributions received to political contributions. The first set of estimates corresponds to the overall average effects, abstracting away from important dimensions of heterogeneity, such as charity sector and ideology. Subsequent specifications allow for this heterogeneity.

The primary structural equation of interest is:

$$\ln(Y_{it(i)}) = \beta_p \ln(P_{m(i)t(i)}) + \beta_x X_{it(i)} + \varepsilon_{it(i)} \tag{1.1}$$

Here, $Y_{it(i)}$ represents one of two possible outcomes: private contributions received by charity i in fiscal year $t(i)$, $Y_{it(i)}$, or fundraising expenses made by that charity in that period, $F_{it(i)}$. $P_{m(i)t(i)}$ represents the sum of political contributions made by individuals in the charity's market, $m(i)$, during $t(i)$, and $X_{it(i)}$ includes a charity-specific fixed effect and a variety of additional controls.

Two sources of endogeneity exist in Equation (1.1). First, for those donors who give to both charities and politicians, their contributions to $Y_{it(i)}$ and $P_{m(i)t(i)}$ are jointly determined.[4] Second, for all potential charitable donors, including those who do not give to politicians, the error term $\varepsilon_{it(i)}$ includes unobservable, latent civic-mindedness among the set of potential donors in a particular charity's market. For these reasons, (1.1) cannot be estimated as-is. This motivates an instrumental-variables approach to estimation. The choice of instrument must be relevant – correlated with $P_{m(i)t(i)}$ – but satisfy a conditional exclusion restriction, which requires that it affect outcomes only

[4] Simultaneity bias in Specification (1.1) may also occur if political campaigns adjust their fundraising efforts in response to anticipated competition from charities. While political fundraisers certainly do behave strategically, it is unlikely that they consider charities to be their primary competitors for donors' contributions. Political campaigns are more likely to formulate an optimal fundraising strategy as a best response to the fundraising strategies of other political campaigns. As they consider other campaigns to be their primary opponents, the actions of charitable fundraisers are unlikely to prove salient to political fundraisers. Indeed, many comprehensive texts describing the behavior of political donors neglect to mention their charitable contributions at all (*Magleby* (2014)). *Magleby* (2019) mentions political donors' charitable giving only in a very narrow context, acknowledging that some believe that contributions made to a charitable foundation closely associated with a political candidate can be viewed as attempts to purchase access to the candidate. Magleby mentions only two specific foundations: the Clinton Foundation and the Foundation for Excellence in Education. Both were linked directly to specific 2016 presidential candidates. Neither file Form 990, and so neither are represented in the data used for the present work. The narrow focus on contributions to candidate-linked foundations, as opposed to charitable contributions in general, suggests that other types of charities are not considered relevant from the perspective of any of the political fundraisers interviewed in Magleby's work. Even if political fundraisers did consider other charities to be competitors for donors' funds, this form of simultaneity is also addressed through the use of an instrument.

through $P_{m(i)t(i)}$, and not through unobservable components of the error term, $\varepsilon_{it(i)}$.

The number of political races held in market $m(i)$ during fiscal year $t(i)$ ($N_{m(i)t(i)}$) satisfies these assumptions. It is clearly relevant: politicians and receive more contributions in the year, and especially in the few months, leading up to an election. The exclusion restriction will be satisfied if the number of elections alone – not weighted by their competitiveness, or the amount of media attention they generate, but simply the amount of seats up for primary, general, or special election to the presidency, House, Senate, or governorship – does not affect the charity's fundraising or contributions through $\varepsilon_{it(i)}$. The number of total seats in each market is determined by the market size – specifically, the number of states in each charity's market. For each charity, the market consists of a fixed set of states, and time-invariant characteristics of the state are therefore captured by charity-level fixed effects.[5] Crucially, the model is estimated on data covering the fiscal years 2012 through 2019, a period which falls between the 2010 Census and 2020 Census. The number of seats in the US House of Representatives fluctuates with the Census' tally of the population by state. While the electoral maps may shift in an intercensal period, the overall number of seats remains the same. The 2010 redistricting maps were in use throughout the country by the time of the 2012 election (*Spencer* (2021)), implying that the total number of political offices remains unchanged within each market over the estimation period. Within each market, the number of seats up for re-election is determined by the baseline length of each elected official's term and the schedule for re-election, both of which are set at the federal or state level and are clearly exogenous to any choices made by the charity. The inclusion of year fixed effects purges $\varepsilon_{it(i)}$ of the aspects of this national election cycle which affect all markets in the same way. Finally, when the number of seats up for re-election deviate from this set pattern, this deviation must be attributable to a sudden death or scandal on the part of the politician. These events are plausibly random, and therefore uncorrelated with $\varepsilon_{it(i)}$.[6] Therefore, the instrument $N_{m(i)t(i)}$ appears to satisfy the exogeneity assumption required of valid instruments.

While the number of races alone should not affect charities' outcomes after controlling for year fixed effects and the population in the charity's market, it is nonetheless possible that as more races

[5] Details of the market construction are discussed in Section 1.4.1.

[6] Note that the instrument varies across charities within the same geographic market, if these charities end their fiscal year in different months.

are held in a charity's market, the greater the probability that one of them is particularly controversial or important. Such a race would draw news coverage or attention in a way which might encourage civic participation among potential donors, independently of any political contributions they make. Take for example the Georgia senate runoff election held in 2020. This close election drew national news coverage, and drew contributions from many out-of-state donors. Suppose some of these donors lived outside the fundraising catchment area for some Georgia-based charity. If their political contributions were used by Georgia-based political campaigns to generate political advertising, and this political advertising affected Georgia-based charitable donors' generosity towards a local charity, then this close race would affect this charity's fundraising or contributions without affecting political contributions made by people who live in its market. This channel would represent a threat to identification, if not shut down. Some control for the national importance of a race is therefore necessary for the exclusion restriction to hold. Races which take on this national importance tend to be close. Unfortunately, the closeness of a race is itself endogenous, as political contributions can be deployed by campaigns to affect turnout and therefore vote share (*Cox and Munger* (1989); *Gerber* (1998); *Kim and Leveck* (2013); *Spenkuch and Toniatti* (2018); *Konstantinou et al.* (2021); *Schuster* (2020)). However, when a politician wins a seat by a small margin, political observers tend to expect the next election for that seat to be close as well (*Levitt* (1994); *Jacobson* (1990)). This enables the use of a proxy variable to control for this potential violation of the exclusion restriction: the number of races which were close during the last general election for a given seat.

The remaining covariates are chosen in order to more precisely identify the effect of political contributions on charitable fundraising and contributions. Several factors will tend to affect both simultaneously, including the the income and amount of potential donors, the relative price of political and charitable giving, and the degree to which these donors pay attention to new political and civic developments. Therefore $X_{it(i)}$ includes the log of market-level population, the log of personal income within the market, the share of tax returns filed within the market with itemized deductions, and the share of people in the market who follow the news. Naturally, some elections – particularly, but not exclusively, presidential elections – may impact fundraising conditions across all markets nation-wide; this motivates the inclusion of year-specific fixed effects.[7] To control for competitive conditions affecting the demand side of the markets for both political and charitable funds, $X_{it(i)}$ includes a variable reflecting fundraisers' annual salaries.

The main specification, (1.1), will be estimated first on the full sample of charities, pooling organizations together across sectors. The National Taxonomy of Exempt Entities classifies charities into five major categories: Arts, Education, Health, Human Services, and Other. This final category includes advocacy groups, environmental groups, religious groups[8], internationally-oriented groups, mutual benefit groups, and public and social benefit groups. Clearly, the activities of some charitable sectors are more closely related to the political sphere than the activities of other sectors. Ideology is also unlikely to be distributed evenly across charitable sectors (see Section 1.6 for further discussion). In order to explore the heterogeneity of these elasticities across sectors, a version of (1.1) will be estimated for each of the five major NTEE groups. Heterogeneity across the ideological spectrum will be examined by estimating (1.1) separately for subsamples of left-leaning, right-leaning, centrist, and non-ideological groups.

1.4 Data

The empirical strategies outlined in the previous section are implemented by merging charity-level data from IRS Form 990 to aggregated political contributions from the Federal Election Commission (FEC), or political advertising data from the Wesleyan Media Project (WMP). These data are aggregated up to match the charity's fiscal year and geographic market. All other variables are assembled in a similar fashion. This section discusses all relevant data sources, including construction of the measure of charity ideology.

1.4.1 IRS Form 990

This paper relies upon electronically filed Form 990 data. Organizations which claim tax exemption under Section 501(c)(3) of the Internal Revenue Code are required to file this annual information return if they are sufficiently large. In particular, public charities which normally bring

[7] These year fixed effects are defined for years ended November, rather than calendar years, to mirror the timing of US elections. While this is not standard, it is particularly appropriate in this context, since the timing of charities' fiscal years varies. See Section 1.4 for further detail on timing.

[8] This sub-category excludes religious congregations, which are not required to file information returns with the IRS.

in at least $50,000 in gross receipts, and hold over $500,000 in total assets at the end of the tax year, are required to file Form 990.[9] Beginning in 2006, the IRS introduced the option to file Form 990 electronically, as opposed to in a paper format. Initially, electronic filing (hereafter, e-filing) was compulsory for all organizations with at least $10 million in net assets, and optional for all other organizations. Take-up of e-filing has increased over time: as of July 2019, all Form 990 returns must be filed electronically. As a result, the universe of electronically filed Form 990s can be thought of as an unbalanced panel. In order to balance this panel, this project includes all organizations observed filing their Form 990 electronically for each fiscal year between 2012 and 2019, inclusive.[10] At the beginning of this period, only 2% of Form 990 filers were required to e-file, but 41.3% opted into e-filing regardless (*Blackwood et al.* (2014)). As a result, this sample covers roughly 80% of charitable contributions made in the United States (*Internal Revenue Service* (2018); *Blackwood et al.* (2014)).

There are trade-offs associated with use of the e-filings, as opposed to traditional paper filings. Historically, research on tax-exempt organizations has relied on a subset of fields from the Form 990 filings of a small sample of tax-exempt organizations. By contrast, the e-filing data contains both the universe of electronic Form 990 filers, and allows the researcher to utilize any field on the form: a clear advantage. The disadvantage of using e-filed Form 990 data comes from the fact that organizations select into e-filing nonrandomly at some point between 2006 and 2019, as the deadline for technology adoption approaches. *Karol* (2023b) confirms that electronic filers are larger than paper filers. This would create negative bias in the estimates if smaller charities are more sensitive to political contributions than larger charities. However, this negative bias attenuates over time, disappearing with universal adoption of the e-filing technology.

Use of the e-filings enables the use of a new method of measuring the charity's market, which represents an improvement in accuracy over previous work. Previous work has relied on digitized paper filings, which admit observation of the charity's mailing address. Past work may therefore consider the relevant geography for a charity to correspond to the borders of the state in which it is

[9] This information return asks charities to disclose far more detail than the Forms 990-EZ or 990-N, which are required of smaller organizations.

[10] The IRS began publishing e-filed Form 990 returns in bulk in 2011, motivating this project's use of data beginning in 2012.

located. However, the charity's market (here defined as the catchment area for its fundraisers) often crosses state lines. In order to avoid biasing estimates in specifications which rely on state-level variation, past work often relies on narrowing the sample of interest to focus on a set of charities likely to operate only within state borders. E-filed data improves on the ability to observe the charity's market because it digitizes the information given in the field which asks charities to "list the states with which a copy of this Form 990 is required to be filed."[11] As of 2020, all but 7 states require charities to file some sort of annual registration with the state government in order to solicit contributions in the state.[12] In many, but not all, cases, these requirements include the filing of a Form 990 or annual report. This set of states can therefore be viewed as the charity's market: it reflects the set of states where it fundraises. However, since not all states require registration in order to legally solicit, and since not all of these states require the Form 990 as part of the solicitation, the markets inferred based on the charity's self-report of the states where it files Form 990 is a weak underestimate of the true set of markets in which the charity operates. To deal with this issue, this paper defines a charity's market in a time-invariant way. A charity's market includes the set of states where the charity has ever fundraised, plus the set of states which do not require annual registration, plus the state in which it is domiciled. Assuming that the charity correctly reports the set of states in which it files in at least one year, this definition of a market should capture all of the states in which a charity solicits contributions, and potentially some states in which it does not do so. This will bias the estimates towards zero. To see why, imagine a regional charity which operates in the South, and solicits contributions only from donors in the region. This charity's fundraising and contributions should not depend on political contributions made in any of the 7 states which do not require annual registration, and so the main estimate of interest will be a weighted mean of these null effects and any non-zero effects of Southern political contributions on fundraising by, and gifts made to, this Southern regional charity.

Apart from geographical information reflecting a charity's market and fiscal year, this dataset is also the source of all outcome variables and several covariates. The key outcome variables used in

[11] This field is Form 990, Section VI, Line 17 in tax years 2012-2019.

[12] These states include Arizona, Delaware, Idaho, Indiana, Montana, Nebraska, South Dakota, Vermont, and Wyoming (*National Association of State Charity Officials* (2021)). Charities must register with the attorney general if they solicit in the state, but they must do so only once.

this study include fundraising expenses and private charitable contributions, though results are also produced for specifications which take total contributions and government grants as outcomes.[13] Private contributions, and therefore total contributions, include donations from individuals, foundations, and other groups, such as corporations and donor-advised funds.

As fundraising is hypothesized to be a crucial mechanism through which political contributions affect charitable giving, an alternative set of results are produced, which restrict attention to organizations which always report positive fundraising expenses. Both the full sample and this fundraiser subsample are balanced by dropping organizations which do not file electronically in all eight fiscal years covering the period between 2012 and 2019, inclusive. Following this process, the full sample includes 487,133 observations of 64,444 unique organizations, observed between fiscal years 2012 and 2019. The fundraiser subsample includes 216,128 observations of 27,016 unique organizations, observed over the same period.

As discussed in Section 1.2.1, the Citizens United decision marked the beginning of a new era of campaign finance. This ruling occurred in 2010, only two years before the beginning of the sample period. It is quite plausible that this landmark decision had dynamic effects on political contributions, which had not yet dissipated by the beginning of this sample period. This may limit the external validity of the estimates.

1.4.2 Federal Election Commission and National Institute on Money in Politics

Data on political contributions comes from two sources: the Federal Election Commission (FEC) and the National Institute on Money in Politics (NIMP). The FEC data covers contributions made by individuals to federal candidates, political parties, political action committees (PACs), and independent expenditure-only committees (super PACs). The NIMP data covers contributions made by individuals to candidates for the position of governor or lieutenant governor. Both data sources include a wealth of information about political donors and their contributions, including the amount and date of the donation, the identity of the recipient, and the donor's name, address, and employer.

[13] In fiscal years 2012–2019, fundraising expenses are found in Part IX, line 25, column D; government grants are found in Part VIII, line 1e; and total private contributions are defined as total contributions (Part VIII, line 1h), minus government grants.

Both federal and state laws require political candidates and organizations to periodically disclose their donors, provided that these donors meet certain aggregate thresholds for disclosure.[14] At the federal level, a donation is recorded in the FEC's Individual Donations Bulk Dataset if the donor makes at least $200 in cumulative contributions to a particular political candidate's committee, party committee, PAC, or super PAC.[15] State aggregate thresholds vary widely, ranging from $0 to $300 (*Campaign Finance Institute* (2018)).

The primary explanatory variable in Specification (1.1) is the total number of political contributions made by potential donors to charity i during its fiscal year. The set of potential donors to a particular charity consists of the people who live in its market. For this reason, the variable of interest is constructed by first aggregating all contributions which meet disclosure thresholds by the donor's state and the month in which they are made. Each market-fiscal year pair consists of a set of states and month-years, and so all that remains to construct the political contributions variable is to sum up contributions by the appropriate set of states and month-years.

This measure of political contributions reflects only giving by large, individual donors. One might therefore consider it to be measured with error. There are three main sources of measurement error: first, the omission of small, individual donors; second, the omission of corporate contributions to super PACs; and third, the omission of individuals' contributions to 501(c)4 "dark money" groups. These sources of measurement error will affect the estimated elasticities if they covary both with the instrument (the number of political races held in the charity's market during its fiscal year) and the outcome (charitable fundraising or giving).

Omission of small individual donations could create negative bias in the estimates; however, to believe this bias represents a substantial portion of the estimate, it must be the case that a large fraction of the covariance between the instrument and the true measure of political contributions comes from this measurement error. *Bouton et al.* (2022) examine the temporal variance of political contributions by small vs. large donors. The authors find that while small donors' contributions

[14]Some recipient organizations report all donations, regardless of whether they meet the threshold for disclosure; these small-dollar contributions are reported separately, in the FEC's Individual Database. The main specifications of this paper are estimated using contributions sourced from the FEC's Individual Donations Bulk Dataset and the NIMP data.

[15]Prior to 2014, the threshold included $200; beginning in calendar year 2015, only contributions strictly greater than $200 were required to be reported.

exhibit greater variance than large donors' contributions, this additional variance is related to "significant events" like conventions and the death of Supreme Court Justice Ruth Bader Ginsburg, and not to the number of races held. This result suggests that the instrument should not covary with this source of measurement error.

Bertrand et al. (2020) finds a positive relationship between corporations' contributions to PACs and corporate foundations' contributions to charities relevant to politicians associated with those PACs. If the relationship between corporations' charitable giving and contributions to super PACs runs in the same direction as the relationship between corporations' charitable giving and contributions to traditional PACs, this form of measurement error should bias estimates towards zero.

The final source of measurement error concerns the omission of contributions to 501(c)4 groups from the measure of political contributions. It is possible that elections change the social context in such a way that charitable donors decide to donate to a 501(c)4 advocacy group instead of to a related charity. This would create negative bias in the results if the number of political races increase contributions to 501(c)4 advocacy organizations, and charitable donors consequently substitute away from donations to related 501(c)3 charities. Identification of 501(c)4 advocacy groups related to 501(c)3 charities is beyond the scope of this work. However, if a given 501(c)3 charity is related to another tax-exempt or taxable entity, it is required to file Form 990 Schedule R. Appendix I re-estimates (1.1), omitting all organizations which file this schedule. These specifications will omit not only organizations with related 501(c)4 advocacy groups, but also many other charities, including those which are only related to other 501(c)3 charities. These results are qualitatively robust to the headline estimates, an outcome which provides assurance that this source of measurement error is not of first-order importance.

1.4.3 CQ Voting and Elections Data

An instrument is required in order to overcome endogeneity concerns in estimating Specification (1.1). As discussed above, this instrument is the number of political races held in a charity's market during its fiscal year. These data come from CQ Voting and Elections Data, and include primary, general, and special elections for the offices of Governor, U.S. Representative, U.S. Senator, and President. Races are summed up to the charity's market-fiscal year level in the same manner as the one used to aggregate political contributions.

As these data include the final vote count by candidate for each election, they may be used to construct the measure of lagged close races described above. A political race is described as close if its margin of victory was less than 20 percentage points. This is a very conservative definition of a close race, intended to cover as many races which could capture media attention as possible.

These data also include information on the number of candidates for a given political seat. This information is used to construct an alternative instrument: the number of uncontested political races held in the charity's market during its fiscal year. Despite being uncompetitive by definition, these races still generate political contributions. This may happen for several reasons. The candidate's donors may still enjoy "warm-glow" or consumption benefits of making these donations. Alternatively, these donors may see their donations as investments in legislative influence, which will pay off with certainty. Robustness checks performed using this redefined instrument are presented in Appendix H.

1.4.4 Wesleyan Media Project

Data on political advertisements comes from the Wesleyan Media Project (WMP). This source provides access to Kantar Media Group data on all political advertisements aired on broadcast television in all 210 Designated Market Areas (DMAs) in the United States. As discussed above, an additional instrument is needed to estimate Specification (1.14). This instrument is derived from WMP's estimates of the average cost per minute to air these advertisements, aggregated up to the charity's market-fiscal year level.

As WMP provides the exact dates on which each ad airs, aggregation to the fiscal year level can proceed in the same manner as aggregation of FEC data or CQ Voting and Elections data. Aggregation to the geographic market level proceeds slightly differently. Of the 210 DMAs in the United States, many traverse state boundaries. Ads which air in multi-state DMAs are coded as airing in each state of the DMA, even if these ads support candidates in other states in the same DMA. This is because such ads can still raise civic awareness among the viewers, even if these viewers are not the intended target audience of the ads.

1.4.5 Charity Ideology

As discussed above, a measure of charity ideology will be helpful in making inferences about donors' motivations. This section describes the procedure employed to measure charity ideology. This method is an adaptation of the procedure outlined in *Gentzkow and Shapiro* (2010), originally used to measure media bias in newspapers. First, I identify a set of ideological phrases using tweets made by US House Representatives. Second, I measure charities' ideology by observing how frequently they use these ideological phrases on their websites.

In the first step, a corpus of text documents produced by members of Congress is parsed into a set of two- and three-word phrases. Gentzkow and Shapiro rely on the text of the 2005 Congressional Record, which captures all speeches made on the floor of the House or Senate in that year. However, common topics of political conversation have changed considerably in the nearly two decades since. In this context, it seems unlikely that political speeches in 2005 have many phrases in common with those used by charities in 2022. This paper therefore relies on a body of text scraped from tweets made by House representatives during the summer of 2022.[16]

Gentzkow and Shapiro measure a House representative's ideology as the share of votes within that representative's district which supported a Republican for president at the last presidential election. With this measure in hand, one can calculate the relative frequencies with which each representative uses each phrase. A set of politically polarizing phrases are selected by using Pearson's χ^2. These phrases were included if they fit the following two criteria: first, they must appear in text produced by at least 50 and not more than 20,000 charities; and second, the absolute value of the χ^2 value calculated for this phrase must be at least 40. 881 phrases fit these criteria, 465 of which are commonly used by Democrats and 416 of which are commonly used by Republicans. The 60 most polarizing phrases in each category are presented in Table 1.1. For each of these 881 phrases, phrase-specific slope and intercept parameters are recovered by regressing the relative frequencies with which congressperson c uses phrase p on the measure of congressperson c's ideology. These

[16] The production of this measure rests on an assumption that charities' ideologies are relatively constant over time. As the charities in question are observed between 2012 and 2019, it is possible that their ideologies have in fact drifted over this time period. Ideally it would be possible to produce time-varying estimates of charity ideology using the same methodology. To do so would require that several historical snapshots of each charity's website be observable. This may be possible, though beyond the scope of the current work. The use of broad ideological categories, rather than a continuous measure of charity ideology, serves to correct for the possibility of ideological change over time.

parameters are used in the second step.

In the second step, a second corpus of text is parsed into two- or three-word phrases. Whereas Gentzkow and Shapiro's text consists of newspaper articles, here the text is collected from charity websites. If a charity has a website, it can list its web address in its Form 990 filing.[17] Each charity's website is retrieved from its Form 990 and crawled to a depth of 2. In other words, the web crawler picks up all text on the organization's homepage, as well as all links on the homepage; it then follows each link and picks up all text found on those pages. This text is then cleaned, tokenized, stemmed, and placed into two- and three-word phrases using the R package *quanteda* (*Benoit et al.* (2018)). The next step is to calculate the relative frequency with which each charity uses each key political phrase. For each phrase, the phrase-specific intercept from step 1 is subtracted from the relative frequency from step 2. For each charity, these differences are regressed on the phrase-specific slope term from step 1. The resulting coefficient represents the charity's ideology.

This produces a continuous measure of charity ideology with extremely long tails. Figure 1.3 depicts the distribution of this measure on a subset of its domain. Ultimately, the most useful measure of ideology for this setting is categorical, rather than continuous. Charities are sorted into four categorical bins according to the following procedure. First, the winsorized mean and standard deviation are calculated, winsorizing this continuous measure of ideology at the 10th and 90th percentiles. Left-leaning values of the ideological measure are defined as those less than one winsorized standard deviation below the winsorized mean; similarly, right-leaning values are defined as those more than one winsorized standard deviation above the winsorized mean. Values within one winsorized standard deviation of the winsorized mean are considered ideologically moderate. Finally, all organizations for which the continuous ideological measure is coded as missing are categorized as apolitical. This is because the ideological measure is not defined for organizations which do not use politically polarizing phrases. If organizations do not engage in political speech, they are considered apolitical. The distribution of the categorical ideology measure is presented in Figure 1.4.

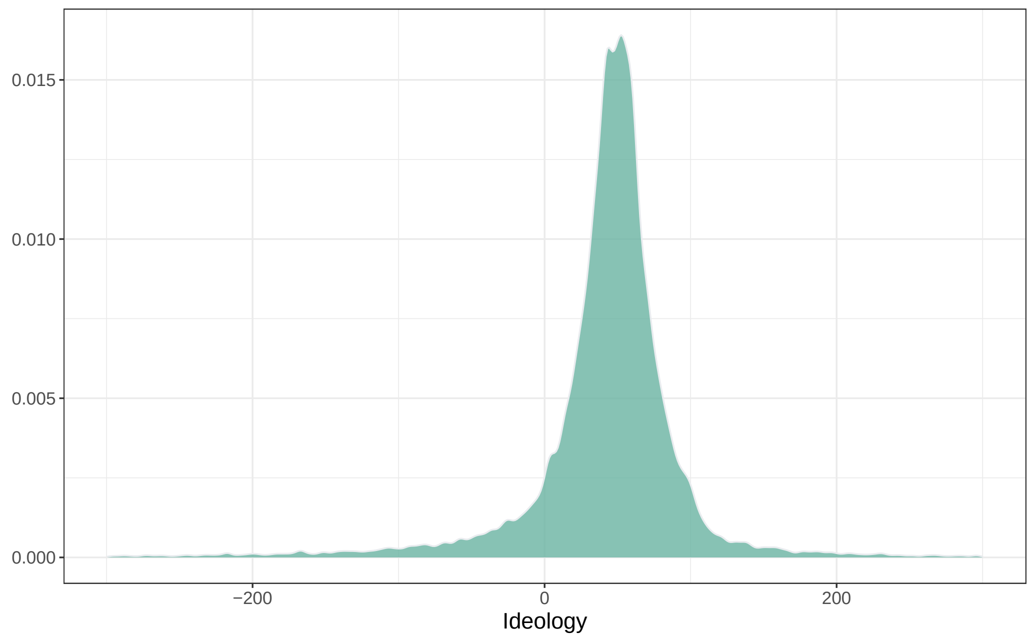
[17] This can be found in the header, on line J.

Table 1.1: Most Partisan Phrases in Congressional Tweets, June-September 2022

Panel A: Phrases Most Often Used by Democrats		
gun* violenc*	clean* energi*	lgbtq* communiti*
health* care*	sign* law*	activ* shooter*
lower* cost*	gun* violenc* prevent*	drug* cost*
climat* chang*	bipartisan* infrastructur*	inflat* reduct*
prescript* drug*	women* health*	reproduct* health* care*
gun* safeti*	women* right*	civil* right*
mass* shoot*	birth* control*	vote* yes*
social* secur*	abort* care*	pass* legisl*
climat* crisi*	drug* price*	protect* right*
reproduct* freedom*	bipartisan* infrastructur* law*	lower* health*
save* live*	vote* right*	fight* climat*
background* check*	student* debt*	combat* climat*
hous* pass*	vote* pass*	health* care* cost*
abort* right*	pay* fair*	care* cost*
reproduct* right*	fair* share*	keep* fight*
violenc* prevent*	get* done*	safer* communiti*
reproduct* health*	climat* action*	scienc* act*
across* countri*	inflat* reduct* act*	protect* abort*
marriag* equal*	right* choos*	public* health*
infrastructur* law*	reduct* act*	protect* act*

Panel B: Phrases Most Often Used by Republicans		
joe* biden*	record* high*	econom* polici*
southern* border*	vaccin* mandat*	one* year* ago*
biden* administr*	green* new*	border* cross*
presid* biden*	govern* spend*	tax* increas*
border* patrol*	green* new* deal*	taxpay* dollar*
illeg* immigr*	new* deal*	per* gallon*
gas* price*	big* tech*	saudi* arabia*
rais* tax*	energi* polici*	econom* crisi*
border* secur*	take* back*	kathi* hochul*
america* first*	war* american*	america* last*
energi* independ*	pregnanc* center*	border* wall*
nanci* pelosi*	amend* right*	busi* deal*
energi* product*	energi* crisi*	brave* men*
god* bless*	white* hous*	pay* price*
presid* trump*	back* hous*	rank* member*
took* offic*	hous* democrat*	save* america*
nation* secur*	high* inflat*	cross* border*
second* amend*	secur* nation*	great* nation*
one* year*	men* women*	spend* bill*
american* peopl*	natur* gas*	brave* men* women*

Notes. Stars represent wildcard characters, allowing for a single phrase fragment to match to a number of specific forms. Underlying text data sourced from Congressional tweets made over a period of 100 days, ranging from May 26, 2022 through September 2, 2022.



Notes: Kernel density estimated for organizations with estimated ideology values in the interval $[-300, 300]$. This omits 970 outliers (2.5% of charities) with non-missing ideology estimates.

Figure 1.3: Kernel Density of Continuous Ideology Variable

This measure of ideology is an example of a "bag-of-words" approach to text analysis, and as such is subject to a number of limitations. In particular, this approach can only identify the valence of words or phrases that appear in a comparison set, regardless of whether this comparison set is a collection of labeled Congressional tweets or a hand-coded set of charities' websites. If charities use different language to express similar ideas to those used by House representatives, these methods will perceive charities as more moderate than they truly are. Furthermore, these methods have difficulty recognizing sarcasm, mockery, or other tonal cues which a human reader may pick up from context. To see how this may become problematic, consider Table 1.1, which notes that two phrases related to the "Green New Deal" are among the top 60 phrases used most often by Republicans. It is unlikely that these mentions are positive in context. However, when this phrase appears on a charity's website, the Gentzkow-Shapiro algorithm will count this as a conservative turn of phrase. This will tend to bias estimates of left-leaning environmental groups' ideologies towards the center. When a phrase is used in earnest by a politician, but is used in a derogatory or mocking way by a charity, it will also create a bias towards centrism in the ideological estimates. As a robustness check, an alternative measure of charity ideology is produced using supervised machine learning techniques. A further description of this measure can be found in Appendix D, along with alternative estimates produced using this measure.

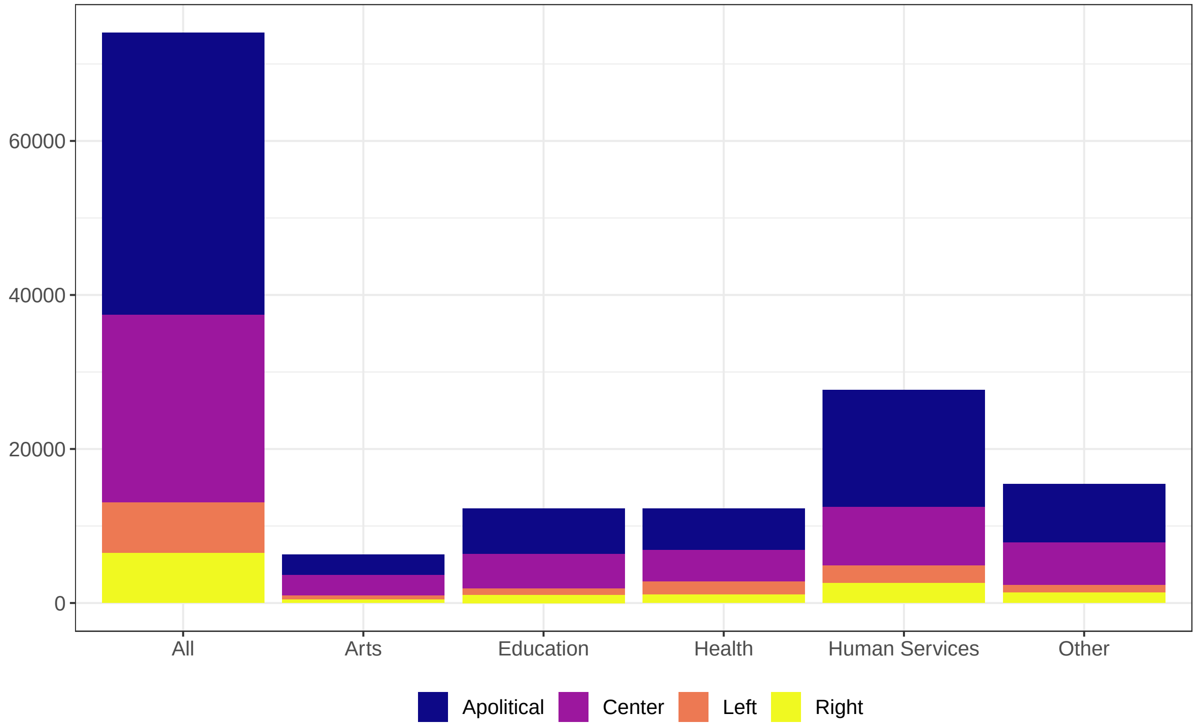


Figure 1.4: Categorical Ideology by Charity Sector

1.4.6 Additional Covariates

Additional covariates come from the Bureau of Economic Analysis, the Bureau of Labor Statistics, the Congressional Election Study (formerly known as the Cooperative Congressional Election Study), Federal Reserve Economic Data (FRED), and the IRS. Data on personal income and population in each state-year come from the BEA's Regional Data Program[18]. Data on average annual salaries of fundraisers come from the BLS' Occupational Employment and Wage Statistics program[19]. The CES includes a question asking respondents how much attention they pay to the news. This question is used to construct a variable reflecting the share of population who say they follow the news some or most of the time.

These variables are observed at the state-year level. However, the charity's market consists of a collection of states, and its fiscal year does not always line up with the calendar year. Some degree of temporal mismatch is inevitable; for variables measured at the annual level, the temporal

[18]Table ID SAINC1.
[19]Occupational code 13-1130.

match occurs by matching the year of observation to the charity's fiscal year. Geographic mismatch is minimized by constructing each control variable as a population-weighted mean of the values observed for each state in the charity's market.

Table 1.2: Summary Statistics

	Mean	St. Dev.	Min.	Median	Max.
Organization-Level Variables					
Fundraising Expenses (Thousands)	217.46	2,117.77	0.00	3.56	256,936.33
Total Contributions (Thousands)	3,704.12	32,802.24	0.00	396.99	3,291,724.54
Private Contributions (Thousands)	2,407.38	25,491.09	0.00	237.56	3,289,029.75
Government Grants (Thousands)	1,296.74	13,521.86	0.00	0.00	1,288,972.56
Total Assets (Thousands)	34,745.84	468,987.31	0.00	1,498.38	74,349,535.08
Total Liabilities (Thousands)	12.83	197.08	0.00	0.13	35,634.84
% Arts Org.	0.10	0.30	0.00	0.00	1.00
% Education Org.	0.18	0.38	0.00	0.00	1.00
% Health Org.	0.17	0.37	0.00	0.00	1.00
% Human Services Org.	0.34	0.47	0.00	0.00	1.00
% Other Org.	0.22	0.42	0.00	0.00	1.00
% Left	0.09	0.29	0.00	0.00	1.00
% Right	0.09	0.29	0.00	0.00	1.00
% Center	0.36	0.48	0.00	0.00	1.00
% Apolitical	0.45	0.50	0.00	0.00	1.00
No. States per Market	10.66	4.54	9.00	10.00	51.00
Market-Level Variables					
Population (Millions)	41.51	40.79	20.50	30.96	328.33
Personal Income (Millions)	1,954,776.55	2,048,574.55	844,235.23	1,391,589.97	17,060,279.79
Political Contrib.	262,809.84	359,280.03	28,406.94	165,417.08	4,397,323.00
% Republican Contrib.	42.59	9.51	15.43	42.39	70.96
% Democratic Contrib.	40.15	8.73	20.87	38.73	70.50
Lagged Close Races	10.69	17.54	0.00	11.00	182.00
Political Races	108.02	137.69	0.00	93.00	1,504.00
Races with Incumbents	58.78	81.56	0.00	50.00	896.00
Races with No Incumbent	49.24	59.24	0.00	41.00	668.00
Fundraisers' Salaries	52.74	3.37	26.14	52.25	61.93
% Itemizers	0.24	0.08	0.07	0.27	0.36
% Follow News	77.74	2.48	71.74	78.30	82.42
# Political Ads	146,471.48	162,733.22	6,175.00	125,385.00	3,949,664.00
Ad Cost per Minute	37.23	62.13	2.36	15.88	217.06

Notes. The data includes 487,133 observations of 64,444 unique charities, observed between fiscal years 2012 and 2019, inclusive. Financial variables measured in thousands of constant 2015 dollars.

Data classifying charities according to their NTEE sector comes from the IRS' Business Master File. Data on number of Form 1040 tax returns filed, along with the amount of these returns which include itemized deductions, come from the IRS Statistics of Income Historic Table 2. These are combined with state-year population estimates from the BEA to produce a population-weighted share of itemized tax returns within a charity's market. All financial variables are deflated to constant 2015 dollars using the CPI, sourced from FRED.

1.5 Average Fundraising and Giving Responses to Political Contributions

The results of Specification (1.1) are presented in Table 1.3. When people living in charity i's market increase their political contributions by 10%, charities reduce their fundraising expenditures by 0.95%. On average, this amounts to $3,660 per charity. For the same increase in political contributions, total contributions received by the charity fall by 0.68%. This is equivalent to a reduction of $24,580 per charity. Total contributions include giving from both private and public sources. Column (3) shows that similar increases in political contributions do not affect the amount of government grants received by charities.[20] On the other hand, private contributions to charity are fairly sensitive to changes in political contributions. The same 10% increase in political contributions made by people living in market $m(i)$ costs charities 0.79% of private contributions, on average. This translates into a loss of $18,800 per charity. This is consistent with a story in which political donors consider political and charitable contributions to be substitutes (*Petrova et al.* (2020); *Cagé and Guillot* (2022)), though it does not necessarily imply that this is the case.

The estimates in Table 1.3 represent the average elasticities across all charities. However, the charity's relationship to political contributions may vary according to the purpose of the organization. Due to the government's role in providing human services, education, and healthcare, many organizations in these NTEE categories may find that their production and fundraising technologies are sensitive to the political environment. The same can be said of environmental groups, which fall in the Other NTEE category. Naturally, some organizations' missions are inherently political: in

[20]This is a reassuring result, for two reasons. First, government grants are typically awarded after a longer-term grantmaking process. Second, it bolsters belief in the instrument: if the timing of grantmaking processes were aligned with the timing of elections, a spurious non-zero effect may have materialized in this column. However, it does not.

particular, civil rights, social action, and advocacy groups work in areas that are typically subject to political discussion. These groups also fall under the Other category. Charities which are directly impacted by the political process in these ways should be more sensitive to political contributions.

Table 1.3: Average Effect on Charitable Fundraising and Contributions

	Log Fundraising	Log Contributions	Log Gov. Grants	Log Priv. Contrib.
Log Political Contrib.	-0.095***	-0.068***	0.007	-0.079***
	(0.022)	(0.015)	(0.022)	(0.017)
Log Personal Income/1000	1.706***	1.951***	2.415***	1.727***
	(0.293)	(0.199)	(0.291)	(0.227)
Log Population/1000	-0.172	-0.359	0.402	-0.000
	(0.485)	(0.343)	(0.512)	(0.388)
Fundraisers' Salaries	-0.001	0.002***	0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	0.003*	0.004***	0.009***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
# Lagged Close Races	0.001***	0.001***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.235***	-0.088	-0.171**	-0.052
	(0.070)	(0.054)	(0.080)	(0.063)
Observations	273,774	520,447	218,834	487,133
No. Groups	39,295	67,779	32,387	64,444
First-Stage F-Stat	634.297	846.068	397.279	790.553
Within R-squared	0.003	0.003	0.010	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Figure 1.5 provides some support for this prediction. Fundraising by organizations in the Health and Other sectors are both sensitive to political giving, with elasticities of -0.229 and -0.201, respectively. Organizations in these categories also receive fewer private contributions when political contributions rise: the elasticity of private charity to political contributions is -0.134 for Health charities, and -0.101 for Other charities. While the point estimates for both outcomes are negative for Arts and Education organizations, these estimates lack precision. Human Services organizations appear different from the others. For these charities, political contributions do not appear to change fundraising expenses, but they do reduce private giving. The elasticity of private charity to political giving is -0.071 in this sector.

While the majority of charitable organizations appear apolitical, many charitable organizations serve ideological purposes. This may occur either because the charity's mission explicitly seeks to advance some particular ideology, or because the charity is formed to support a cause which becomes politicized. Previous work has theorized that donors' ideology should influence their generosity. It follows that charitable and political donations may not only be two alternative expressions of the same pro-social preferences: they may represent two alternative expressions of the same ideological preferences.

Table 1.4 presents elasticities of charitable fundraising and giving to aggregate political contributions, allowing for heterogeneity in the charity's ideology. Both left-leaning and politically moderate organizations reduce fundraising and receive fewer private contributions when political contributions rise. In particular, the elasticity of private contributions to political contributions is -0.134 at left-leaning organizations, and -0.092 at politically moderate charities. Elasticities estimated for apolitical and right-leaning organizations lack sufficient precision to be empirically distinguishable from zero. In both cases, the point estimates are negative.

Based on the point estimates, apolitical organizations appear to be the least sensitive to political contributions of all four ideological subsamples. Wald tests reveal that the elasticity of charitable to political giving are marginally smaller at apolitical organizations than at left-leaning organizations ($p = 0.093$) or at centrist organizations ($p = 0.109$).[21] However, it is not possible to detect significant differences in this elasticity between right-leaning groups and apolitical groups. Table 1.4 therefore provides some evidence that ideology plays a role in determining the relationship between political and charitable giving. However, this role is not limited to ideologically extreme organizations: politically moderate charities are also affected.

How large are these within-charity effects? A back-of-the envelope calculation, presented in Appendix E, asks: what would have happened to private charitable giving if political donors had

[21] These marginal differences persist despite the fact that the Gentzkow-Shapiro algorithm will erroneously classify ideologically extreme charities as apolitical, so long as they do not use the same phrases as politicians do to describe their own ideologies. This misclassification should bias the estimates for apolitical groups away from zero. As a result, Table 1.4 understates the differences between the elasticities measured for politicized and apolitical groups.

given an additional \$1 billion to political committees during the 2015-2016 cycle? The estimates presented in Table 1.3 imply that in this scenario, aggregate private charitable giving would have fallen by \$2.9 billion. This figure represents 0.7% of total private charity in the United States in 2016 (*Giving USA Foundation* (2017)). While this decline in private charity is a drop in the bucket relative to the baseline amount of charitable giving, it is quite large relative to the volume of political giving in the US. On aggregate, \$1 of political contributions crowds out nearly \$3 in private charity.

When considering the magnitude of this crowd-out, it is natural to wonder how much of this response is temporary. Given the cyclical nature of political contributions, these estimates may capture delays in giving, rather than a decline in giving, and that charitable giving will rise again in subsequent periods. This possibility is addressed in Appendix L, which demonstrates that increases in political giving in one fiscal year do not lead to increases in charitable giving in the next fiscal year.

To the extent that private charitable giving creates a social benefit, these results indicate that political contributions create disproportionate social harm. This harm exists regardless of political contributions' perceived or actual ability to influence democratic outcomes, or the direction in which these outcomes may be swayed. What can be done about this? Some campaign finance restrictions have recently been lifted by the Supreme Court, on the grounds that they create a burden on free speech (*FEC v. Ted Cruz for Senate*); additional quantity restrictions, or price changes associated with the imposition of a tax, would likely be ruled unconstitutional for the same reason. However, temporary adjustments to the price of charitable giving remain in the realm of possibility. These may be particularly actionable given the cyclical nature of campaign finance. Appendix A illustrates how political contributions affect the optimal subsidy for charitable giving, and derives conditions under which this subsidy rate will rise.

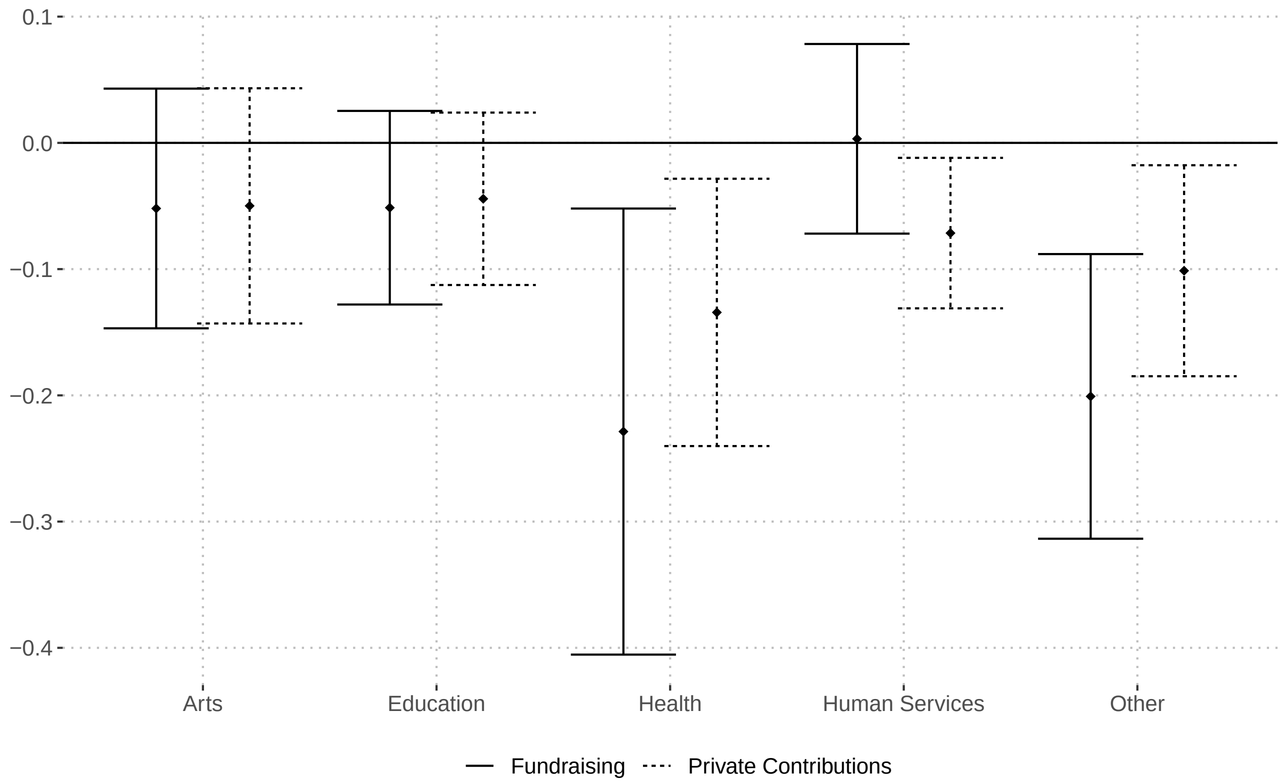
This section has established that political contributions reduce private giving to the average charity. The magnitudes of the estimated elasticities are small. However, when one aggregates across all charities in the sample, the dollar value of the loss in private charity is nearly three times the increase in political contributions. This disproportionate loss in private charity suggests there may be strong spillover effects at play in this context, in which political donors' contributions

Table 1.4: Elasticities of Charitable Fundraising and Contributions by Ideology

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Political Contrib.	-0.214**	-0.065	-0.076***	-0.077	-0.134**	-0.087	-0.092***	-0.028
	(0.095)	(0.089)	(0.027)	(0.051)	(0.055)	(0.065)	(0.026)	(0.030)
Log Personal Income/1000	3.589***	1.126	1.521***	1.023*	2.489***	1.294	2.001***	0.949**
	(1.063)	(1.149)	(0.386)	(0.606)	(0.739)	(0.830)	(0.353)	(0.370)
Log Population/1000	-1.083	0.686	-0.471	0.938	-0.736	0.431	0.000	0.566
	(1.679)	(1.660)	(0.651)	(0.913)	(1.332)	(1.299)	(0.586)	(0.617)
Fundraisers' Salaries	-0.003	0.003	-0.003***	0.002	0.000	-0.002	-0.000	0.002*
	(0.004)	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
% Follow News	0.002	0.001	0.003	0.000	0.002	-0.003	0.003	-0.001
	(0.005)	(0.005)	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
# Lagged Close Races	0.003**	0.001	0.001***	0.001	0.002*	0.001	0.001***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
% Itemizers	-0.003	0.084	-0.192*	-0.228*	-0.172	0.257	-0.023	-0.050
	(0.242)	(0.200)	(0.099)	(0.127)	(0.230)	(0.193)	(0.096)	(0.110)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710
First-Stage F-Stat	24.496	29.139	563.395	98.336	51.255	41.946	572.092	206.535
Within R-squared	0.002	0.006	0.014	-0.000	0.001	0.002	0.004	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

can affect charitable giving by non-political donors. In particular, if political donors substitute between political and charitable giving, the expected return to charitable fundraising should fall. The resulting change in charitable fundraising may result in fewer contributions made by all donors. A sufficient, but not necessary, condition for the return to charitable fundraising to fall would obtain if political donors' contributions increase campaign activity, which in turn affects the generosity of non-political donors. The rest of the paper will explore these spillover effects.



Notes: Error bars represent 95% confidence intervals. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Figure 1.5: Average Effect on Charitable Fundraising and Contributions, by Sector

1.6 The Charity's Strategic Response to Political Giving

The previous section shows that charities adjust their fundraising strategy in response to political contributions made by their potential donors. This section explores why this fundraising response occurs. It begins by developing a model of charitable fundraising in the presence of political contributions, and finds that the charity's fundraising response can be decomposed into three distinct channels. Some of these channels can affect the flow of charitable contributions from donors who do not contribute to politicians, and so are not substituting between political and charitable giving.

Consider a one-period model of charitable fundraising, presented in Equation (1.2). In the spirit of *Rose-Ackerman* (1982), a representative charity holds an ideological position, θ, on some one-dimensional spectrum of ideology. This charity chooses fundraising F_θ to maximize its objective function, which includes two terms: a charitable production function C, increasing and concave in net revenues $(Y_\theta - F_\theta)$, and a term capturing the charity manager's distaste for fundraising, $\Psi(F_\theta)$.

$$\max_{F_\theta}\{C(Y_\theta(F_\theta, P) - F_\theta; d(\theta, \alpha(P))) - \Psi(F_\theta)\} \tag{1.2}$$

Y_θ represents the aggregate quantity of gifts made to the charity indexed by θ, from all donors in the economy.[22] Y_θ depends on the charity's fundraising expenditures.[23] The charity should only spend \$1 on fundraising if they expect to get at least \$1 back in contributions. This implies that the derivative $\frac{\partial Y_\theta}{\partial F_\theta}$, called the marginal productivity of fundraising (MPF), must be greater than or equal to 1. The MPF can be equivalently understood as the return on the charity's fundraising expenses. In addition to this restriction on the sign and magnitude of the MPF, it is assumed to fall in fundraising expenses. Diminishing returns to charitable fundraising obtain for two reasons. First, as in *Rose-Ackerman* (1982) and *Name-Correa and Yildirim* (2013), charities are able to rank potential donors according to expected generosity, and approach them in descending order of the expected yield of the appeal. Solicitations sent to the $n + 1$st donor will necessarily bring in less revenue, on net, than solicitations sent to the nth donor. Second, as donors have a distaste for excessive fundraising (*Andreoni and Payne* (2003); *Gregory and Howard* (2009); *Gneezy et al.* (2014); *Meer* (2017); *Andreoni et al.* (2017); *Charles et al.* (2020)), the marginal productivity of funds spent to solicit a particular donor should fall in spending.

Y_θ also depends on P, a vector of political contributions. Recall that Y_θ is the total value of all gifts received by the charity, and therefore represents the sum of gifts made by political and

[22] Donors' gifts are optimally chosen as solutions to a constrained utility-maximization problem.

[23] The nature of this relationship builds on insights from *Name-Correa and Yildirim* (2013): since fundraising is costly, the charity will strategically choose to fundraise from "net contributors".

non-political donors to the charity. This expression can equivalently be represented as:

$$Y_\theta(F_\theta, P) = sY_\theta^p(F_\theta, P) + (1 - s)Y_\theta^n(F_\theta, P) \tag{1.3}$$

where the superscript p refers to political donors, and the superscript n refers to non-political donors. The share of political donors among the charity's potential donors is represented by s.[24] $Y_\theta^p(F_\theta, P)$ then refers to the value of contributions made to the charity by donors who also support politicians, whereas $Y_\theta^n(F_\theta, P)$ refers to the value of contributions the charity receives from non-political donors. Each of these objects is assumed increasing in its donors' cumulative willingness to give. If political donors substitute between political and charitable contributions, then their willingness to give will fall, and it follows that charitable contributions from these donors may fall in P.

However, it is also possible that P affects non-political donors' willingness to give, and therefore their charitable contributions. For example, these donors' generosity may be affected by the output of political campaigns. One such effect has been documented by *Hungerman et al.* (2018), which finds a small increase in donations to Catholic churches following a local campaign stop by a Republican presidential candidate. However, campaign stops are not the only output of political campaigns. These campaigns also produce copious amounts of solicitations, sent by mail, email, and text. Even though these solicitations are, by definition, unsuccessful at raising funds from non-political donors, they may nevertheless affect these donors' charitable contributions by generating fatigue. Donors who receive too many solicitations may begin throwing out or ignoring further fundraising appeals (*Diamond and Noble* (2001)). While the phenomenon of donor fatigue is thought to be short-lived, lasting no longer than a week (*Donkers et al.* (2017)), the sheer volume of solicitations sent by political campaigns may multiply the fatigue donors experience. This paper will examine the effects of another type of campaign output, political advertising, in detail.

The charity's ideological position, θ, enters its production function via $d(\theta, \alpha(P))$. This term represents the ideological distance between the charity's ideological position and the prevailing political environment, $\alpha(P)$. Importantly, political contributions do not need to affect the outcome

[24]Note that s may vary with the number of seats up for election.

of a general election or a particular vote in order to alter the political environment. They may do so by affecting political challengers' entry decisions (*Hamm and Hogan* (2008)), by changing the winner of a primary election (*Kalla and Broockman* (2018)), or influencing elected officials' decisions to kill bills before they leave committees (*Powell* (2014)).

The charity's production technology is state-dependent, and the ideological distance term captures the state on which it depends. Charities operate within some institutional environment, which may be very welcoming and supportive of the charity's mission, or it may be quite hostile to that mission. Suppose this distance term takes values in the unit interval. If the government and the local community completely oppose the charity, then $d(\theta, \alpha(P)) = 1$. In this case, the government may use its power to largely or completely prevent the charity from producing its good or service. If the charity draws the ire of the community, community members may physically prevent the charity from operating, either through direct confrontation, or by declining to supply the charity with volunteers. In these cases, no matter how much net revenue the charity brings in, its output level is fixed at or near zero.[25] Mathematically, this implies the derivative of the charitable production function, $\frac{\partial C}{\partial(Y_\theta - F_\theta)}$, would be equal to zero. This expression is called the marginal productivity of charitable spending, or MPCS. On the other hand, suppose the charity were perfectly aligned with the government and community, and $d(\theta, \alpha(P)) = 0$. In this scenario, the government and the charity agree both on the set of goods and services which must be provided and the manner of provision, and compete to provide them to end users. While this competition may result in some optimal mix of public and private charitable provision, the marginal productivity of charitable spending in this case may be relatively lower than in an intermediate case, where there is some disagreement between the government, the public, and the charity. The relationship between the marginal productivity of the charity's spending and the ideological distance between the charity and the government must therefore be nonlinear.

[25] One such example is the case of Whole Woman's Health Alliance, a 501(c)3 nonprofit which provides abortion care in areas of the country where access to these services is low. While the MPCS at Whole Woman's Health may be quite high – in particular, this may be the case if the organization creates extensive-margin changes in access for some communities – the Texas legislature passed S.B. 8 in May 2021, preventing all abortion clinics in the state from providing these services after 6 weeks of pregnancy. This legislation dramatically reduced the MPCS of Whole Woman's Health and other abortion providers in Texas, as they faced near-total bans on service provision. These bans became total in the summer of 2022, when the overturn of Roe v. Wade enabled pre-Roe trigger laws to take effect.

The charity's objective function (1.2) implies the following comparative statics. Subscripts are suppressed for notational convenience.

$$\frac{\partial F}{\partial P} = -\frac{(\frac{\partial^2 C}{\partial (Y-F)^2}\frac{\partial Y}{\partial P} + \frac{\partial^2 C}{\partial (Y-F)\partial P})(\frac{\partial Y}{\partial F} - 1) + C'(Y-F; d(\theta, \alpha(P)))\frac{\partial^2 Y}{\partial F \partial P}}{C''(Y-F; d(\theta, \alpha(P)))(\frac{\partial Y}{\partial F} - 1)^2 + C'(Y-F; d(\theta, \alpha(P)))\frac{\partial^2 Y}{\partial F^2} - \Psi''(F)} \tag{1.4}$$

The denominator is negative, as F maximizes (1.2). The sign of the relationship between political contributions and fundraising is therefore given by:

$$sign\Big(\frac{\partial F}{\partial P}\Big) = sign\Big(\Big(\overbrace{\frac{\partial^2 C}{\partial (Y-F)^2}\frac{\partial Y}{\partial P}}^{\substack{\text{Fundraising-Constant} \\ \Delta \text{ Production}}} + \overbrace{\frac{\partial^2 C}{\partial (Y-F)\partial P}}^{\Delta MPCS}\Big)\underbrace{\Big(\frac{\partial Y}{\partial F} - 1\Big)}_{nMPF} + \underbrace{\frac{\partial C}{\partial (Y-F)}}_{MPCS}\overbrace{\frac{\partial^2 Y}{\partial F \partial P}}^{\Delta MPF}\Big) \tag{1.5}$$

The first term inside the parentheses is the fundraising-constant change in charitable production. This term captures the change in charitable production that would follow if political contributions brought about changes in aggregate charitable giving, in the absence of any change to the charity's fundraising strategy.

The second term inside the parentheses is the marginal change in the MPCS caused by political giving. The MPCS is affected by political giving only if these political contributions change the political environment, and the sign of this term depends on the ideological distance between the charity and its government. If these political contributions make the political environment less unfriendly to the charity, the marginal productivity of contributions will rise. However, if the political environment becomes too friendly to the charity, the marginal productivity of contributions may fall again, as the charity has less value to add.

The sum of the first two terms is multiplied by the net marginal productivity of fundraising (nMPF). As discussed above, the nMPF must always be positive, since the charity will be unwilling to spend a dollar in fundraising if it does not expect to gain at least a dollar in charitable contributions.

The third term is the product of the MPCS and the marginal change in the MPF caused by political giving. The MPCS must always be positive, since the charity's production function is increasing in its net revenue. With more resources, it may produce more of its services. The second term in this product represents the change in the marginal productivity of fundraising attributable to political contributions. In theory, political contributions could either raise or reduce the return to charitable fundraising. In practice, if it is the case that political donors substitute between political and charitable giving, then the return on a dollar of fundraising targeted at these donors will fall in political giving. Previous work suggests that high-income donors are more expensive to solicit than lower-yield donors (*Alston et al.* (2021)), as successful solicitations of these donors require more personalized fundraising strategies than are necessary for lower-income donors. These high-income donors are several times more likely to give to politicians than the general population (*Cook et al.* (2014)), and simultaneously give a larger share of their income to charity than those at lower rungs of the income distribution (see *Meer and Priday* (2021) for a summary of the literature). It follows that higher-yield donors to the charity may become even more expensive to solicit during political campaigns, as these donors may be disproportionately likely to give large sums to politicians as well.

Furthermore, charities may have difficulty identifying which of its potential donors will give to politicians; therefore, all else equal, the return to a dollar of fundraising aimed at any donor will fall in expectation. Even in the event that charities correctly guess exactly which of its potential donors will give to politicians, frictions may still prevent the charity from adjusting their fundraising strategies in a targeted way.[26]

In summary, political contributions may affect charitable fundraising through three avenues. Each of these effects are theoretically ambiguous in sign, and therefore the direction of each effect becomes an empirical question. The next section describes and implements the empirical strategy for estimating these effects.

[26]Even if the charity is able to perfectly observe the donor's type, the marginal productivity of fundraising may still fall. The reasoning lies in the charity's fundraising strategy. Following *Name-Correa and Yildirim* (2013), the charity chooses an optimal "fund-raiser set," consisting of all donors who would be "net contributors" to the charity if solicited. If some of these net contributors substitute away from charitable giving, and towards political giving, the net revenue gained from contacting each such donor will fall. In some cases, it may even become negative. The charity may want to contact new donors, who are more likely to become net contributors, since they would like to consume the charitable good but can no longer free-ride off of others' generosity. The presence of competing political contributions therefore reduces supply of contributions by some donors in the charity's former donor set, but may also affect others' willingness to give, and the direction of the effect is unclear. If the lost donations come from a few very generous donors, and the new donations come from a larger set of less generous donors, then the marginal productivity of fundraising is likely to fall.

1.7 Components of the Fundraising Response

This section outlines and implements the empirical strategies for estimating two objects of interest discussed in the previous section. These include the fundraising-constant change in private charity, as well as the marginal productivity of fundraising. This section further discusses how results may be interpreted to make inferences about the effect of political contributions on the marginal productivity of charitable spending.

1.7.1 Empirical Strategy

Section 1.6 shows that political contributions can affect charitable contributions through three distinct channels. The first is the fundraising-constant change in private charity; the second is the marginal productivity of charitable fundraising; and the third is the return to charitable fundraising, or MPF. In order to estimate the second channel, it would be necessary to compile data on charitable production. This exercise is beyond the scope of the current paper. This section outlines a strategy for leveraging the present dataset to estimate the remaining two channels.

Consider the following system of equations:

$$\ln(F_{it(i)}) = \beta_p \ln(P_{m(i)t(i)}) + \beta_x X_{it(i)} + \varepsilon_{it(i)} \tag{1.6}$$

$$\ln(Y_{it(i)}) = \gamma_P \ln(P_{m(i)t(i)}) + \gamma_F \ln(F_{it(i)}) + \gamma_{PF} \ln(P_{m(i)t(i)}) \times \ln(F_{it(i)}) + \gamma_x X_{m(i)t(i)} + \nu_{it(i)} \tag{1.7}$$

Within this system, Equation (1.6) is identical to (1.1), and (1.7) is an augmentation of that original specification. This augmented version of (1.1) includes fundraising as an additional endogenous variable, and interacts this with the original endogenous regressor, political contributions.

The addition of a new endogenous explanatory variable requires the use of an additional instrument. Following *Andreoni and Payne* (2011) and *Heutel* (2014), the organization's total liabilities at the beginning of the fiscal year is employed as an instrument for fundraising expenses. If a charity carries additional liabilities on its balance sheet – in particular, if it accumulates debt – then all else equal, it will be more motivated to fundraise in order to cover those liabilities. This settles the question of instrument relevance; but does this instrument satisfy the exclusion restriction? The instrument would fail the exclusion restriction if the charities' liabilities could affect its private contributions through some channel besides charitable fundraising. It is possible that potential donors may consider key indicators of the charity's financial performance when deciding which organizations to support, and some of these indicators depend on total liabilities. However, the results are robust to inclusion of the liabilities-to-assets ratio, which is the only major indicator to depend directly on liabilities (*Mayo* (2022)). The instrument for the interaction term is formed by interacting the instrument for fundraising expenses with the instrument for political contributions.

How do these estimates correspond to the channels described in Section 1.6? Begin by taking a derivative of Equation (1.7) with respect to $\ln(F)$. Suppressing subscripts, applying elasticity formulae, and rearranging, this gives:

$$\frac{\partial Y}{\partial F} = \frac{Y}{F}(\gamma_F + \gamma_{PF}\ln(P)) \tag{1.8}$$

This object is the marginal productivity of fundraising, if political contributions were held constant. It represents the amount of contributions a charity receives per dollar spent on fundraising. Per the model, the MPF must always be greater than 1, and will tend to be much larger than 1 if charity managers derive disutility from fundraising.

Repeat, taking a partial derivative of (1.7) with respect to $\ln(P)$:

$$\frac{\partial Y}{\partial P} = \frac{Y}{P}(\gamma_P + \gamma_{PF}\ln(F)) \tag{1.9}$$

This expression represents the partial effect of political contributions on charitable giving to charity i, holding fundraising constant. In other words, this object reveals how much revenue charity i would have lost, had it not changed its fundraising strategy.

Finally, take a second derivative of Equation (1.8) with respect to P:

$$\frac{\partial Y}{\partial F \partial P} = \frac{\gamma_F + \gamma_{PF}\ln(P)}{F}\left(\frac{\partial Y}{\partial P} - \frac{Y}{F}\frac{\partial F}{\partial P}\right) + \frac{Y}{PF}\gamma_{PF} \tag{1.10}$$

Therefore, a procedure to recover the change in the MPF consists of first estimating Equations (1.6) and (1.7), recovering the relevant coefficients, and then plugging them into the expressions in Equations (1.8) - (1.10). These specifications are estimated only for organizations which report strictly positive fundraising expenditures in each year. Equation (1.9) represents the fundraising-constant change in private charity. Equation (1.10) represents the change in the MPF. Standard errors are recovered via the delta method.

1.7.2 Results

The first row of Table 1.5 represents the baseline marginal productivity of fundraising, which is the yield to the charity, in dollars, of spending an additional $1 on fundraising.[27] As expected, these estimates are positive and much larger than unity. This finding is consistent with previous work, which takes the finding that the MPF exceeds 1 as evidence that charities are not revenue-maximizers, but rather derive disutility from fundraising (*Steinberg* (1986); *Andreoni and Payne* (2011); *Heutel* (2014); *Meer and Priday* (2021)).

In the absence of a fundraising response, the average charity might have gained $325 per million dollars of political contributions made in its market. This counterfactual gain is not statistically distinguishable from zero. The 95% confidence interval of the change in private contributions the average charity would experience per $1 million in political contributions ranges from a loss of $532 to a gain of $1,812. The positive sign of this average effect is due to organizations in the Health and Other sectors. After holding fundraising constant, political contributions raise private giving to Other-sector organizations by $1,906 per million dollars. This effect is marginally significant. Political contributions appear to encourage giving to Health-sector organizations as well, though this effect is somewhat smaller and less precisely estimated than its Other-sector counterpart. In each of the remaining sectors – Arts, Education, and Human Services – the point estimates of the fundraising-constant change in private charity are negative, but not statistically significant. At Human Services organizations, this effect is distinguishable from zero at the 15% level.

Had these charities not changed their fundraising strategies, to what extent would political contributions have crowded out private charity? The answer is obtained by plugging the bounds of the 95% confidence interval for the results produced in the second row of Table 1.5 into an analogous back-of-the-envelope calculation to the one described in Section 1.5. This exercise reveals that a

[27] The estimates of Equations (1.6) and (1.7), which form the basis of the estimates presented in Table 1.5, are presented in Appendix F.

dollar given to a political campaign crowds out no more than \$1.73 per dollar, and may crowd in as much as \$3.85 per dollar. Note that this confidence interval encompasses both estimates of crowd-out produced by *Petrova et al.* (2020), the only other set of crowd-out estimates yet produced using data for the United States[28]. When this exercise is repeated, including charities which fundraise in at least one year, this confidence interval ranges from a loss of \$1.50 charitable contributions per dollar of political contributions, to a gain of \$6.07 charitable contributions per dollar of political contributions.[29]. In both cases, the estimate of crowd-out produced using the headline results lies far below the lower bound of the confidence interval for the fundraising-constant change in private charity. This implies that changes in charities' fundraising strategies generate the vast majority, if not the entirety, of the observed crowd-out.

However, it does not follow that charities should simply fundraise more. This reduction in fundraising appears rational. This is visible in the third row of Table 1.5, which shows how political contributions affect the marginal productivity of fundraising. On average, when political contributions rise by \$1 million, the return to charitable fundraising falls by \$0.23. This is a small share of the baseline MPF estimate presented in the first row, but nevertheless it has a discouraging effect on charitable fundraising.

Taken together, the estimates in rows 2 and 3 of Table 1.5 suggest that if the average charity had not cut back on fundraising, it might not have lost private contributions. Nevertheless, the yield of fundraising expenses falls in political contributions. These expenses are already an undesirable use of the charity's funds, and during a campaign, they become less effective at generating revenue. Therefore the charity will find it optimal to forgo some of these fundraising expenses, even though it ends up sacrificing some private contributions, on net.[30]

[28] *Petrova et al.* (2020) produce two estimates of the crowd-out of charitable contributions by political contributions. Based on observational data, it finds that \$1 in political giving crowds out \$0.08 in charitable giving. Based on experimental data, it finds that \$1 in political giving crowds out \$0.68 in charitable giving.

[29] For details, see Appendix K.

[30] See Appendix N.

Table 1.5: Estimated Components of Fundraising Response

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	39.988***	24.257***	27.879***	23.338***	46.176***	56.625***
	(2.472)	(4.938)	(5.408)	(3.967)	(5.226)	(5.639)
$\frac{\partial Y}{\partial P}$	0.325	-0.296	-0.628	0.977	-1.122	1.906*
	(0.437)	(0.805)	(1.589)	(1.202)	(0.782)	(1.011)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.231***	-0.116	-0.079	-0.288**	0.011	-0.570***
	(0.050)	(0.074)	(0.059)	(0.122)	(0.129)	(0.160)
Observations	203,317	25,638	35,919	26,886	67,786	47,088
No. Groups	26,341	3,285	4,644	3,500	8,753	6,159

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

The negative effect on the MPF is particularly strong for organizations in the Health and Other sectors, where estimates imply the MPF falls by over 1%.[31] At the same time, these are the only two sectors in which the first-order, fundraising-constant effect of political contributions on private charity is positive, and in which fundraising expenses fall in political giving. Equation (1.5) can shed further light on these organizations' behavior. Assume that political contributions have no direct impact on the marginal productivity of the charity's spending.[32] In this case, it is clear that for Health and Other charities, each of the remaining two summands on the left-hand side of Equation (1.5) will be strictly negative, so long as the charity's production function is increasing and concave in its inputs. In other words: if fundraising were held constant, political contributions may increase private charitable giving. However, if the charity's production function is concave, then this rise in contributions will generate a less-than-proportional increase in charitable output. This weakens the charity's incentive to fundraise, concurrent with a drop in the return to its fundraising.

[31]To see this, divide the estimate in row 3 by the estimate in row 1.

[32]It is reasonable to expect that this assumption is too strong, particularly for organizations in the Other sector. The assumption is placed solely for the purpose of clear discussion. So long as the charity's MPCS does not increase enough to outweigh the negatively-signed fundraising-constant change in charitable production, the left-hand side of Equation (1.5) will remain the sum of two negative terms.

Human Services charities, like those in the Health and Other sectors, lose private contributions to political donations. However, Table 1.5 reveals that the mechanisms which underlie this relationship are quite different for Human Services charities, compared to Health- and Other-sector charities. Political contributions have a very small, very imprecisely estimated, positive-signed effect on the marginal productivity of fundraising at these charities. In this sector, the return to fundraising is just as effective as ever, regardless of the volume of political contributions made by the charity's potential donors. Recall from Figure 1.5 that the elasticity of fundraising to political contributions is approximately zero at Human Services charities. As these charities spend a nonzero amount on fundraising, this implies $\frac{\partial F}{\partial P} \approx 0$. Yet the point estimate in Table 1.5 suggests that by holding their fundraising expenses constant, these charities may miss out on quite a lot of contributions: Human Services charities may lose \$1,122 private contributions per \$1 million political donations.[33] Then why not fundraise more? Once again, the model can shed some light on charities' reasoning. Per Equation (1.4), the following expression must hold:

$$0 \propto \Big(\frac{\partial^2 C}{\partial(Y-F)^2}\frac{\partial Y}{\partial P} + \frac{\partial^2 C}{\partial(Y-F)\partial P}\Big)\Big(\frac{\partial Y}{\partial F} - 1\Big) + \frac{\partial C}{\partial(Y-F)}\frac{\partial^2 Y}{\partial F \partial P} \tag{1.11}$$

From Table 1.5, we learn that at Human Services charities, $\frac{\partial Y}{\partial F} \approx 46$, $\frac{\partial Y}{\partial P} \approx -1.122$, and $\frac{\partial^2 Y}{\partial F \partial P} \approx 0$. Plugging in estimates from Table 1.5 gives:

$$0 \propto \Big(\frac{\partial^2 C}{\partial(Y-F)^2} \cdot (-1.122) + \frac{\partial^2 C}{\partial(Y-F)\partial P}\Big) \cdot 45 + \frac{\partial C}{\partial(Y-F)} \cdot 0 \tag{1.12}$$

$$= \Big(-1.122 \cdot \frac{\partial^2 C}{\partial(Y-F)^2} + \frac{\partial^2 C}{\partial(Y-F)\partial P}\Big) \cdot 45 \tag{1.13}$$

Concavity of the charitable production function implies $\frac{\partial^2 C}{\partial(Y-F)^2} < 0$. Given this assumption and these estimates, it must be the case that $\frac{\partial^2 C}{\partial(Y-F)\partial P} < 0$ as well. That is, these estimates imply that political contributions have a negative effect on the charitable production technology at human services organizations. As discussed in Section 1.6, this must happen because political contributions

[33] The 95% confidence interval for this estimate ranges from a loss of \$2,655 to a gain of \$411; the point estimate is statistically significant at the 15% level.

change the ideological distance between a charity and the political environment. On average, in this sample, the changes to this ideological distance term harm the charity's ability to turn its resources into human services.

For all charities other than Human Services charities, the marginal productivity of fundraising falls. This constitutes a spillover effect in the sense that because charities may not be able to differentiate political donors from non-political donors. A drop in the return to the next dollar of fundraising therefore causes them to cut back on fundraising from all donors, including some who do not provide financial support to politicians.

1.7.3 The Role of Political Television Advertising

The previous section has illustrated that the return to charitable fundraising falls in political contributions. Why might this occur? There are two types of donors to a given charity: those who give to politicians, and those who do not. If, as previous work finds, political donors substitute between political and charitable contributions, then these donors' willingness to give will fall in political giving. Therefore the charity's return on a dollar of fundraising targeted at political donors will fall in political giving, as well. However, political donors are a relatively small percentage of the voting-age population. For the average charity to cut back on fundraising by nearly 10%, as estimated in Section 1.5, one of two alternatives must be true. Either political contributions reduce political donors' willingness to give to an extremely large extent, or political contributions also make non-political donors' less willing to give to charity.

Why might this be? When a political donor gives a dollar to a campaign, the campaign must put the dollar to some use. Often, the campaign uses its funds to purchase political advertising. These political ads are aimed at broad swaths of the electorate, including those who do not give to politicians. Their purpose is to inform and persuade voters, as well as to increase voter turnout. Voting and political engagement may be considered pro-social actions, and therefore the charitable donors represented in the electorate may decide whether and how to participate in the political process, jointly with their decision about whether and how to support charities. By engaging the public in taking these political actions, political campaigns may therefore inadvertently discourage giving to charity. In this way, political campaigns' public-facing activities may affect non-political donors' willingness to give to charity as well.

This section explores this possibility by introducing a control for political campaigns' public-facing activities. Political television ads are chosen as a measure of these activities, because they are the single largest category of campaign expenditures, and they are also the part of the campaign that is most visible to voters (*Fowler et al.* (2016)). The importance of this channel will be captured by the extent that a control for political television advertising moderates the estimated elasticity of private charitable contributions to political contributions.

1.7.3.1 Empirical Strategy

The elasticity of charitable giving to political contributions, net of the effect of political advertising, can be recovered by estimating the following specification:

$$\ln(Y_{it(i)}) = \gamma_P \ln(P_{m(i)t(i)}) + \gamma_A \ln(A_{m(i)t(i)}) + \gamma_X X_{it(i)} + \varepsilon_{it(i)} \tag{1.14}$$

where $A_{m(i)t(i)}$ is the volume of ads which play in market $m(i)$ in fiscal year $t(i)$. Equation (1.14) is estimated jointly with Equation (1.1), on a common sample. Comparison of γ_P from Specification (1.14) with β_P from Specification (1.1) enables an assessment of the relative importance of inputs and outputs of the political campaign's production function.

As discussed above, political contributions are endogenous in specifications such as (1.14) because donors may make their political and charitable contribution decisions jointly. If the number of political ads aired in the charity's market during its fiscal year rises in the amount of political contributions made by the residents of that market-year, this variable will include an endogenous component as well.[34] Therefore it is prudent to treat $\ln(A)$ as endogenous in (1.14), and instrument for $\ln(A)$ using the average cost to air an ad per minute.

At time of writing, the relevant advertising data are available through the 2018 election cycle. Therefore Specification (1.14) is estimated for fiscal years ended December 2018 and earlier. This specification is estimated jointly with a version of Specification (1.1), in which data is restricted to share a common sample with (1.14).

[34] Since the number of political ads is chosen by the campaign or other political group, rather than by individual charitable donors themselves, it is possible that this variable is less endogenous than the political contributions variable.

1.7.3.2 Results

The estimates discussed in the previous section are presented in Table 1.6. The estimates in Panel A correspond to β_P from Equation (1.1), while those in Panel B correspond to γ_P from Equation (1.14).[35] Panel C presents the difference between unconditional and conditional elasticities.

In most sectors, a substantial proportion of the effect of political contributions on charitable giving is moderated by exposure to political TV ads. In the Arts sector, the entire effect is explained by political ads.

Once again, the Human Services sector is an exception to the rule. Political ads explain the smallest share of the effect for the Human Services sector, and the elasticity net of political ads is still statistically different from zero in this sector.

Why might campaign outputs moderate the relationship between political and charitable giving to such a large extent? It may be the case that exposure to political television advertising causes non-political donors to substitute between taking pro-social actions in the political sphere, and engaging in the pro-social behavior of charitable giving.[36] If this is the case, then political contributions may reduce all charitable donors' willingness to give to charity. For political donors, this substitution occurs directly, as these donors allocate their own contributions across alternative avenues for influencing public good provision. For non-political donors, this substitution operates indirectly, obtaining because political contributions finance political ads, and these political ads influence their pro-social behavior. If political contributions reduce all donors' willingness to give to charity falls, then it follows that the return to charitable fundraising falls as well. Future research will be needed to verify the mechanism by which political contributions affect non-political donors' charitable giving.

[35] Note that while the estimates in Panel A are conceptually identical to the elasticity estimates presented in Section 1.5, they differ because estimates in Table 1.6 are produced using data that spans a shorter time period.

[36] Not all of this non-financial political activity need be productive; even pure political hobbyism (*Hersh and Schaffner* (2017)) may produce this kind of substitution.

Table 1.6: Political Ads Account for Majority of Overall Effect

	All	Arts	Education	Health	Human Services	Other
	Panel A: Elasticity, Gross of Political Ads					
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.082***	-0.085	-0.042	-0.103**	-0.076**	-0.112***
	(0.018)	(0.053)	(0.050)	(0.047)	(0.031)	(0.037)
	Panel B: Elasticity, Net of Political Ads					
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.020	0.022	0.015	-0.035	-0.041*	-0.033
	(0.012)	(0.033)	(0.032)	(0.035)	(0.022)	(0.025)
$\frac{\partial \ln(Y)}{\partial \ln(A)}$	-0.081***	-0.109**	-0.099	-0.112**	-0.034	-0.112**
	(0.019)	(0.048)	(0.071)	(0.057)	(0.025)	(0.044)
	Panel C: Difference					
$\Delta\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.062***	-0.107**	-0.057	-0.068**	-0.036	-0.079***
	(0.014)	(0.046)	(0.040)	(0.034)	(0.026)	(0.030)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

1.8 Conclusion

This paper sheds light on the relationship between political and charitable giving. In doing so, it documents an under-appreciated social cost of political contributions. While previous work shows that these contributions have scope to affect the political process in a very limited set of circumstances, their impact on charitable giving is clear and negative. In particular, this paper finds that the average within-organization elasticity of private charitable giving to political contributions is -0.079. This is consistent with previous findings that political donors view charitable and political giving as substitutes (*Petrova et al.* (2020); *Cagé and Guillot* (2022)). However, this negative effect is not only a product of within-donor changes in giving patterns. Political contributions reduce the return to charitable fundraising, which in turn causes the charity to cut back on its fundraising expenses. Charities therefore miss out on contributions from both political and non-political donors.

While this may seem like a small within-charity elasticity, its cumulative impact is quite large. Per a back-of-the-envelope calculation, this elasticity implies that a dollar of political contributions crowds out \$2.90 of private charitable contributions. The majority of this crowd-out is attributable to changes in charitable fundraising: if charities had held fundraising constant, charities would have lost no more than \$1.50 per dollar, and a null hypothesis of zero crowd-out cannot be rejected. These results highlight the importance of the charity's fundraising response to political contributions, a margin unexplored in previous work.

When paired with a model of optimal charitable fundraising in the presence of political contributions, these results imply that charitable production depends on the ideological distance between the charity and the political environment. This distance can change even if charities themselves are not particularly ideological. While ideologically extreme charities – particularly those on the left – appear more sensitive to political contributions than apolitical charities, political donations still reduce private contributions received by ideologically moderate groups. Further research is needed to explore the role of ideology in this relationship, and in determining charitable production more broadly.

This work advances our understanding of the effect of the political process on voluntary public good provision, and points to many avenues for future work. Whereas this paper has focused on the relationship between financial support provided to charities and political committees, both entities can receive gifts of time as well as money. A more complete characterization of the interplay between charitable and political contributions could consider whether charitable donors trade off non-financial forms of political participation with charitable giving or volunteering. Furthermore, more work is needed to provide direct evidence as to the effect of the political environment on charities' production functions. Finally, these results suggest that reforms to campaign financing may have important consequences for charities which fundraise within those jurisdictions.

With political polarization on the rise, and individuals' political contributions growing at an ever-faster pace, it is crucial to understand the impact of the political environment on charitable giving and production. This paper provides further evidence that these trends will have a damaging impact on charitable contributions. It also identifies which charitable sectors are particularly sensitive to changes in political giving, and provides some insight into the mechanisms which produce these effects. This information should prove useful to policymakers, grantmakers, and charity managers, who can take steps to counteract the resulting loss in charity resources.

CHAPTER II

Bridging the Gap: The Role of the Charity in Voluntary Public Good Provision

2.1 Introduction

Standard models of voluntary public good provision – alternatively called charity – follow *Samuelson* (1954). A representative donor derives utility from a public good, which can be funded using contributions from the government, private actors, or a combination of the two. These standard models therefore describe the behavior of a charitable donor who simultaneously consumes the charitable good to which they donate. It is easy to imagine a real-world example of a charity where the same individual might appear as both a donor and a client: this arrangement neatly describes many museums, schools, and hospitals. These organizations satisfy the legal definition of charity set out by Section 501(c) of the United States Internal Revenue Code. However, they do not always satisfy the more colloquial definition of a charity: an organization set up to provide for those in need (*Cambridge University Press* (2022)). This definition describes food banks, shelters for the unhoused, foster care service providers, and many others. These organizations are also considered charities under Section 501(c). Unlike a museum or a theater, it would be highly unusual for these charities' donors to consume the services produced by these organizations. The standard models of voluntary public good provision therefore fail to describe donation behavior at the charities set up to serve the most vulnerable members of society.

This paper fills that gap in the literature by developing a model of the interactions between donors, recipients, and charities which provide a service in which donors and recipients are two distinct actors. As many motivating examples are organizations which use funds raised from the well-to-do to support those less fortunate, the distinction between donors and recipients in this model arises from differences in their resources. The distinction between donors and recipients will therefore be exacerbated by income inequality and social stratification.

The purpose of this model is to ask how donors would respond to recipients' unmet needs, when donors may have low awareness of recipients' social and economic conditions. This response is related to, but distinct from, traditional notions of crowd-out, which is the main focus of both the theoretical and empirical literature that follows from *Samuelson* (1954). These models (for example, *Warr* (1983), *Bergstrom et al.* (1986), *Andreoni* (1990)) are primarily concerned with private donors' supply responses to changes in others' supply of the public good, but remain silent on the question of how supply of this public good changes with demand by non-donors.

In the model, donors derive warm-glow utility from making charitable contributions to charities which serve the poor. This warm glow increases in inequality between donors and recipients – when this inequality is made salient to donors. By fundraising, the charity can raise this salience. The model makes a surprising prediction about donors' responsiveness to changes in recipients' unmet needs. When recipients' circumstances worsen, donors are less likely to give to charities which support them. This perverse tendency can be overcome if the charity steps up its fundraising efforts, reminding donors of their moral commitments.

This paper proceeds to verify the predictions of this model in the context of the food assistance industry. Unmet need for food assistance is measured by food insecurity. This charitable cause is of particular interest for two reasons. First, nutrition is a basic physiological need. Previous research shows that food insecurity is associated with a vast array of negative outcomes for both mental and physical health (*Gundersen et al.* (2015a)). For adults and the elderly, the negative effect of food insecurity on nutritional outcomes operates independently of the correlation between food insecurity and poverty (*Bhattacharya et al.* (2004)). Second, food insecurity is a pervasive and persistent problem in the United States. In 2020, an estimated 10.5% of the American population experienced food insecurity at some point of the year (*Coleman-Jensen et al.* (2021)). The pandemic has brought a great deal of much-deserved awareness to the ongoing crisis of food insecurity in the United States, but this issue does not typically command attention in the news cycle. The mundane nature of this national emergency implies that at baseline, its salience to the donor class is often low. Charitable organizations looking to raise funds to help the food-insecure may therefore have great scope to raise donors' awareness of the problem.

The empirical analysis of the relationship between donors, recipients, and charities in the context of food insecurity begins by identifying the set of charitable providers of food assistance. These charities are identified using Guidestar's Philanthropy Classification System, which yields a set of 1,389 unique charities, observed between the years 2013 and 2018. On average, these organizations increase fundraising by 0.9% when food insecurity rises by one percentage point. By contrast, private contributions to these organizations do not appear responsive to the prevalence of food insecurity in the geographic area served by the charity. While the point estimate characterizing the overall response of private giving to food insecurity is positive, it falls into negative territory after controlling for changes in the charity's fundraising expenses. The effect of food insecurity on donors' private contributions is not statistically distinguishable from zero, regardless of whether it is expressed as gross or net of fundraising. This indicates that in the most optimistic scenario, donors appear insensitive to food insecurity, unless the charity's additional fundraising prompts them to give more. Further results illustrate that rising food insecurity generates more charitable fundraising, and therefore more private contributions, in states where income inequality is rising as well.

When compared to the predictions of the model, these empirical estimates imply that the "warm glow" donors derive from making charitable contributions does increase in inequality. This would seem to suggest that donors' generosity will always increase in recipients' unmet need. However, the estimates demonstrate that this additional generosity should not be taken for granted. In the context of the American food assistance industry, donors' generosity will increase only if the charity also steps up its fundraising. This is because hunger is not very visible to those who do not experience it, and so its salience to the donor class will be low, in the absence of some informational intervention.

The paper proceeds as follows. Section 2.2 outlines the contribution to the literature. Section 2.3 develops a model of the interaction between donors, recipients, and charities in the voluntary provision of goods and services in demand by low-income people. Section 2.4 describes the empirical strategy used to estimate several key relationships which arise from the model, using data sources described in Section 2.5. Section 2.6 presents and interprets the empirical results. Section 2.7 concludes.

2.2 Contribution to the Literature

Standard models of voluntary public good provision follow *Samuelson* (1954), *Warr* (1983), *Bergstrom et al.* (1986), *Andreoni* (1990). These models demonstrate that if donors' income remains unchanged, then so will voluntary provision of the public good. In each of these models, so long as donors receive some altruistic utility from total public good provision and believe that their own gift is large enough to affect the overall level of provision, then each donor's choice of gift depends on the gifts – and therefore the income – of all other donors. Previous work has used this fact to argue that the income distribution should affect charitable contributions. However, while these workhorse models successfully show that donors' gifts depend on the way income is distributed among donors, these models predict that donors' gifts will be invariant to changes to the income distribution which affect only non-donors.[1]

This case may be particularly important in an environment of rising income segregation. If donors to, and recipients of, charitable provision come from different parts of the income distribution, then these previous models imply that a shock to recipients' incomes, but not donors' incomes, should result in a level of public good provision which is unchanged or greater than before. If recipients' unmet needs fall in their incomes, then this is equivalent to suggesting that donors' contributions to the public good should not fall, and may rise, in recipients' unmet needs. The present work addresses this question.

This work builds upon the model of *Duquette and Hargaden* (2021). In that model, the authors impose the assumption that donors believe their contributions are small relative to the public good. However, donors do derive a private benefit, or "warm glow," from their own charitable gift.

[1] In particular, *Bergstrom et al.* (1986) proves an assertion that changes to the income distribution which affect only donors will weakly increase overall public good provision. The proof of this assertion depends on these two key assumptions. First, donors must receive some marginal benefit from the total level of public good provision, not only their own gift. Second, donors must believe that their own gift can affect total provision. Appendix P shows that in the absence of these two assumptions, which are likely inappropriate for the context of this paper, the proof does not go through. In this case, total public good provision may fall, even when the income redistribution leaves the aggregate income of donors unchanged.

This warm glow depends upon the entire income distribution, not only the segment of the income distribution from which donors are drawn. The present work innovates upon this framework by noting that donors may have trouble observing the shape of the income distribution, or the needs of those who derive income from a different part of that distribution, without an informational intervention by the charity. Whereas Duquette and Hargaden find that charitable contributions fall in income inequality, this paper comes to a different, though complementary, conclusion. The donor derives a greater marginal benefit of giving when they perceive the recipient's needs are greater. An increase in income inequality, coming from changes in the recipient's portion of the income distribution, will simultaneously increase the recipient's unmet needs and reduce the donor's ability to perceive those needs.

This result is particularly consequential in light of recent work, which shows that donors' altruism relies in part on the donor's attitudes towards inequality, as well as their sense of social connectedness, affinity, or empathy for the recipients of their gifts (*Buckley and Croson* (2006), *Small and Simonsohn* (2008), *Derin-Güre and Uler* (2010), *Uler* (2011), *Payne and Smith* (2015), *Mastromatteo and Russo* (2017), *Duquette and Hargaden* (2021)). The bulk of this literature comes to the theoretical conclusion that charitable giving should rise in inequality, though empirical results are mixed. In an environment characterized by increasing income segregation (*Reardon et al.* (2018)), high-income and low-income households may both become isolated from the mainstream of American society (*Krivo et al.* (2013)). One natural consequence of this growing social isolation is that potential donors may become less aware of, or less concerned with, recipients' needs. This paper contributes to the growing literature on the relationship between inequality and charity by estimating the extent to which local measures of inequality may affect the generosity of the relatively high-income towards the relatively low-income, when demand for charitable nutritional aid increases among the latter group. In doing so, it rationalizes the disconnect between papers which predict that inequality should raise donors' generosity, and those which find that this result is not always discernible in empirical work. Economic inequality will simultaneously increase recipients' unmet needs, and reduce donors' ability to perceive these needs.

Depending on the type of charitable good or service, donors may not always have trouble understanding the needs of recipients. Previous research on the response to changes in demand for specific types of charitable services has thus far focused mainly on disaster relief (*Smith et al.* (2017), *Evangelidis and Van den Bergh* (2013), *Eckel et al.* (2007), *Simon* (1997), *Lilley and Slonim* (2016), *Deryugina and Marx* (2020)), which is made highly salient to donors via news coverage. These studies find that private donations exhibit a large and positive response to natural disasters, which is exacerbated by news coverage of these events. *Smith et al.* (2017) find that the death toll of a natural disaster is more strongly related to donations for its victims than the count of people affected by the disaster, suggesting that even when donors are well aware of the conditions which create demand for charitable services, their donative behavior is not closely related to the magnitude of the demand for charity. However, this means that innovations to demand for services which are too mundane for the news cycle – such as nutritional assistance – may not be made salient to donors at all.

In the food assistance context, private charity is regarded as an imperfect substitute for public assistance by end users. Despite the fact that food insecurity is associated with a plethora of negative health outcomes (*Gundersen et al.* (2015a)), takeup of charitable food assistance is quite limited. *Pruitt et al.* (2016) find that only 21.7% of adults living in food-insecure households received charity food. While stigma plays a role in reducing take-up of these services (*Edin et al.* (2013), *Fong et al.* (2016), *Byrne* (2021)), food banks[2] represent an important supplement to public nutrition assistance.[3] *Si* (2018) finds that households become 19.9% more likely to use food bank services in response to a negative income shock, and that living in close proximity to a source of charity food increases take-up. This result clearly implies that changes in unmet need will noticeably alter the size and composition of an anti-hunger charity's clientele. If these changes are significant from the perspective of the charity providing this assistance, this charity may be more likely to communicate this news to its donors, in the hope of keeping or increasing their contributions.

2.3 Donors, Charities, and Clients in the Market for Charitable Funds

This paper contributes to the literature on charitable giving by modeling the behavior of charities, their donors, and their clients as these organizations seek to use donors' funds to provide social

[2] Food banks represent one sub-category of food assistance organizations.

[3] *Byrne* (2021) finds that the number of unique visitors to a food bank network in Colorado increases sharply in the second half of the month, whereas SNAP benefits are paid out between the 1st and 10th of each month.

services to their clients. This model departs from previous work by imposing the restriction that charitable donors and recipients hail from two distinct portions of the income distribution. Owing to the differences in their material circumstances, they also maximize different objective functions. This section first describes the recipient's problem, followed by the donor's problem and the charity's problem. Finally, it derives comparative statics, which describe donors' responses to changes in demand for social services they fund, but do not consume.

2.3.1 The Recipient's Problem

A mass of R identical recipients each solve the following constrained optimization problem:

$$\max\{\max_{x_R,c} u_R(x_R,c) - s \text{ s.t. } y_R = p_c c + x_R; u(y_R,0)\} \tag{2.1}$$

The stigma costs, s, are distributed according to cumulative distribution function $H(s)$, defined on the domain $[0,\infty)$. The price of the charitable good, p_c, represents the monetary value of the individual-specific time, transportation, or effort costs involved in procuring charitable good c. If the value of the first argument exceeds the value of the second argument, the recipient takes up the charitable good with probability t. The charitable good, c, is assumed inferior, and takeup is assumed to decline in income y_R as well.[4] For individuals who take up the charitable good, the ideal consumption of charity (c^*) is given by:

$$u_{R1} p_c = u_{R2} \tag{2.2}$$

As each recipient's first-order condition (2.2) is identical, each will want to consume the same c^*. However, the actual amount of the charitable good available to recipients is given by $G - F$. This is the sum of donors' charitable contributions, G, net of the fundraising expenses the charity incurs to raise this amount, F. The charity provides an equal amount of its good to all recipients who wish to take it up. This realized level of consumption is given by $\bar{c} = \frac{G-F}{Rt}$. Unmet need is

[4]These assumptions hold as long as $\frac{\partial^2 u_R}{\partial c^2} < p_c^2 \frac{\partial^2 u_R}{\partial x_R^2}$ and $\frac{\partial u_R(y_R - p_c c, c)}{\partial x_R} < \frac{\partial u_R(y_R,0)}{\partial x_R}$. The former assumption can be interpreted to mean that the marginal utility of the charitable good diminishes at a much faster rate than the marginal utility of the purchased good. The second assumption is satisfied if the marginal utility of the purchased good is greater when one does not rely on charity at all; like the first assumption, this is consistent with a negative cross-partial, $\frac{\partial^2 u_R}{\partial x_R \partial c} < 0$.

defined by the difference $c^* - \bar{c}$, shown below as a function of net charitable contributions, $G - F$:

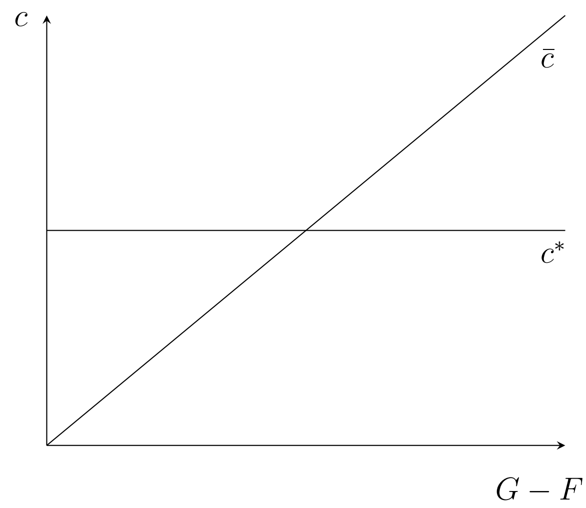


Figure 2.1: Unmet Need

For any $G - F < Rtc^*$, the recipient's desired consumption of the charitable good will exceed their actual consumption, and there will be unmet need. When y_R falls, c^* and t both rise; the increase in takeup raises the denominator of $\bar{c}$. Unless $G - F$ rises, there will be even less of the charitable good to go around, and unmet need will increase.

2.3.2 The Donor's Problem

Assume a mass of D identical donors. For a given donor, preferences can be expressed as follows:

$$u(x_D) + v(g_D, \sigma(F, y_D - y_R)(Rtc^* - G + F)) \tag{2.3}$$

These donors receive utility from private consumption, u_D, as well as a warm-glow utility from their own charitable gift, g_D.[5] Following *Duquette and Hargaden* (2021), the warm glow depends on the broader social and economic context. In particular, the donor's gift can generate more warm-glow utility when the charitable recipient's unmet needs rise – provided, of course, that the donor is aware of these needs. This awareness is captured by the salience function, $\sigma(F, y_D - y_R)$, defined on the unit interval. The greater the income inequality between the donor and recipient

[5]While G is assumed to be the sum of all donors' gifts, such that $G = Dg_D$, donors do not internalize the effect of their own gift on total contributions to the charity. This total volume of charitable contributions may enter the donor's objective function if the donor derives altruistic utility from total provision. However, this term will fall out of the first-order condition, as donors assume $\frac{\partial G}{\partial g_D} = 0$.

class $(y_D - y_R)$, the less salient recipients' needs are likely to be to donors. Through its fundraising expenses, the charity can increase the donor's awareness of the recipient's unmet need.

The donor maximizes (2.3) subject to the budget constraint $y_D = x_D + p_g g_D$, where p_g represents the tax-inclusive price of charitable giving. The first-order condition of the donor's problem is given by:

$$-u'(y_D - p_g g_D)p_g + v_1(g_D, \sigma(F, y_D - y_R)(Rtc^* - G + F)) = 0 \tag{2.4}$$

By appealing to the implicit function theorem, and noting that total gifts to the charity are given by $G = Dg_D$, expression (2.4) yields the following relationship between total charitable contributions and the charity's fundraising, shown in Equation (2.5). The arguments of the warm-glow and salience functions are suppressed for notational convenience.

$$G'(F) = -\frac{Dv_{12}(\sigma_1(Rtc^* - G + F) + \sigma)}{u''(y_D - p_g g_D)p_g^2 + v_{11}} \tag{2.5}$$

The denominator of this expression will be negative, so long as the donor's flow utility function $u(x_D)$ is concave in private consumption, and their warm-glow function is concave in charitable giving. In the numerator, $Rtc^* - G + F > 0$ if unmet need exists among recipients. If charitable fundraising has any power to raise the salience of this unmet need, then $\sigma_1 > 0$. The salience function is assumed weakly positive. Finally, for charitable fundraising to be productive ($G'(F) > 0$), it must be the case that $v_{12} > 0$: the marginal warm glow a donor receives from giving to charity must increase in unmet need.

Expression (2.4) can also reveal how charitable contributions will respond to changes in recipients' resources, absent a change in charitable fundraising:

$$\frac{\partial G}{\partial y_R} = -\frac{Dv_{12}(-\frac{\sigma_2}{y_D}(Rtc^* - G + F) + \sigma R\frac{\partial tc^*}{\partial y_R})}{u''(y_D - p_g g_D)p_g^2 + v_{11}} \tag{2.6}$$

If fundraising is held constant, then the change in giving is proportional to:

$$-\frac{\sigma_2}{y_D}(Rtc^* - G + F) + \sigma R \frac{\partial tc^*}{\partial y_R}$$

The second summand is negative, as takeup of the charitable good falls as recipients' incomes rise. The first summand will be positive, as salience falls in social distance. Then the sign of $\frac{\partial G}{\partial y_R}$ is theoretically ambiguous. As recipients' incomes fall, donors will become less generous if the loss in salience, weighted by the volume of unmet need, exceeds the salience-weighted increase in takeup.

Note that if salience falls in social distance, then $\frac{\partial G}{\partial y_R}$ will be most negative when social distance is small, and least negative when social distance is large. In other words, donors should be most responsive to changes in recipients' unmet needs when inequality is low, and least responsive when it is high.

These results illustrate that while donors are well-intentioned, it is by no means certain that they would increase their generosity when recipients need it most, without the intervention of a charity. If fundraising is allowed to vary with recipients' resources, then the total change in charitable giving can be expressed as:

$$\frac{dG}{dy_R} = \frac{\partial G}{\partial F}\frac{\partial F}{\partial y_R} + \frac{\partial G}{\partial y_R} \tag{2.7}$$

The overall change in resources available to provide social services to the recipient class therefore depends on how the charity responds to changes in recipients' incomes.

2.3.3 The Charity's Problem

The charity chooses its fundraising expenses to solve the following problem:

$$\max_F \left\{ -(Rtc^* - G(F) + F) - \psi(F, y_D - y_R) \right\} \text{ s.t. } G(F) \geq F \tag{2.8}$$

The charity derives disutility from unmet need among the recipient class. The second summand, $\psi(F, y_D - y_R)$, represents the charity's distaste for fundraising. It is increasing in its first argument, F. If the charity finds fundraising less distasteful in an environment of greater inequality, then the cross-partial ψ_{12} will be negative.

Letting λ represent the Lagrange multiplier for the charity's budget constraint, the charity's first-order condition is given by:

$$G'(F)(1+\lambda) - \psi_1(F, y_D - y_R) = 0 \tag{2.9}$$

This in turn implies:

$$\frac{\partial F}{\partial y_R} = -\frac{\frac{\partial G'(F)}{\partial y_R} + \psi_{12}(F, y_D - y_R)}{G''(F)(1+\lambda) - \psi_{11}(F, y_D - y_R)} \tag{2.10}$$

The denominator will be negative so long as the second-order condition holds.[6] The numerator includes two summands. The first term will be negative if fundraising is less successful when recipients are better-off financially. As mentioned above, the second term will be negative if the charity is less hesitant to fundraise when society is more unequal. Then charities should fundraise less as recipients' incomes rise and unmet need falls.

This model provides a framework for decomposing and interpreting the effects of exogenous changes in recipients' unmet need on donors' contributions and charities' fundraising expenses.[7] The following section outlines the empirical strategy for estimating these objects.

2.4 Empirical Strategy

The previous section illustrated the mechanisms through which recipients' unmet need may affect provision of charitable goods and services. This section develops an empirical framework for estimating these mechanisms.

[6] F will be a well-defined maximand so long as disutility does not decay too quickly:

$$\psi_{11}(F, y_D - y_R) > G''(F)(1+\lambda)$$

[7] Note that increases in recipients' income, unaccompanied by changes in donors' income, represent exogenous decreases in unmet need.

2.4.1 Cumulative Effects of Food Insecurity on Contributions and Fundraising

Consider the two outcomes of interest discussed above: fundraising expenses and private contributions. Each outcome y_{ist} can be represented as follows:

$$y_{ist} = \exp(\beta_H H_{ist} + \beta_X X_{ist} + u_{ist}) \tag{2.11}$$

Due to the frequency with which zeroes may appear in the fundraising variable, Equation (2.11) is estimated using a Poisson pseudo-maximum likelihood estimator. The Poisson specifications are estimated using the *ppmlhdfe* command (*Correia et al.* (2020)), a quasi-maximum likelihood estimator. When the likelihood function belongs to the linear exponential family, quasi-maximum likelihood estimators consistently estimate the parameters of the conditional mean function; while the conditional mean must be correctly specified, this estimation method is robust to other forms of distributional misspecification (*Gourieroux et al.* (1984),*Imbens and Wooldridge* (2009),*Wooldridge* (2014)).

Unmet need is measured as the food insecurity rate in the state where charity i is headquartered, H_{ist}. As charities' expenditures during period t cannot alter food insecurity rates at the beginning of that period, state-level food insecurity rates are taken as exogenous from the perspective of charity i.

Specification (2.11) includes a vector of state- and organization-level controls, X_{ist}. This vector includes organization and year fixed effects, as well as a measure of local income. Organizations may fundraise more, and receive more private contributions, in higher-income states. At the same time, income is negatively correlated with food insecurity. It is clearly necessary to control for some measure of local income; but which measure is most appropriate? Measures of income among non-poor households are most appropriate in this context, as it is more relevant for the relationships between food insecurity and fundraising, private contributions, and government budgets. Measures of income that are too closely correlated with either the food insecurity rate or the poverty rate may result in inappropriately large standard errors. Therefore, the local measure of income included in these specifications is the log of average income among households above 500% of the poverty line.

Finally, many specifications include a measure of state-level income inequality, as well as its interactions with unmet need.

2.4.2 Decomposing the Private Charitable Response to Hunger

While Equation (2.11) can be used to produce estimates of the overall effect of food insecurity on fundraising and private contributions, Equation (2.7) illustrates that the latter effect is a function of the former. A decomposition of the overall effect of food insecurity on private contributions into its component parts yields insights into the extent of the charity's ability to raise donors' awareness of recipients' circumstances. This decomposition is accomplished by estimating the following system of equations:

$$y_{ist} = \exp(\beta_f \ln(f_{ist}) + \beta_H H_{ist} + \beta_X X_{ist} + u_{ist}) \tag{2.12}$$

$$f_{ist} = \exp(\gamma_Z Z_{ist} + \gamma_H H_{ist} + \gamma_X X_{ist} + \nu_{ist}) \tag{2.13}$$

where y_{ist} represents private contributions, f_{ist} represents fundraising, and Z_{ist} is an explanatory variable appearing in Equation (2.13) and not Equation (2.12). Note that Equation (2.13) is equivalent to:

$$\ln(f_{ist}) = \gamma_Z Z_{ist} + \gamma_H H_{ist} + \gamma_X X_{ist} + \nu_{ist} \tag{2.14}$$

Therefore the first-stage equation can be written such that the disturbance term is additively separable from the explanatory variables. Since this is the case, it is possible to estimate this system using a control-function approach (*Blundell and Powell* (2003), *Wooldridge* (2014), *Wooldridge* (2015)). This requires the following set of assumptions:

$$(u_{ist}, \nu_{ist}) \perp\!\!\!\perp (H_{ist}, X_{ist}, Z_{ist}) \tag{2.15}$$

$$\mathbb{E}(u_{ist} | H_{ist}, X_{ist}, Z_{ist}) = 0 \tag{2.16}$$

$$\mathbb{E}(\nu_{ist} | H_{ist}, X_{ist}, Z_{ist}) = 0 \tag{2.17}$$

$$\gamma_Z \neq 0 \tag{2.18}$$

These assumptions will be satisfied if the excluded instrument, Z_{ist}, has a strong relationship to f_{ist}, and affects y_{ist} only through f_{ist}. *Andreoni and Payne* (2011) argues that the occupancy costs faced by a charity fit this description – all else equal, charities which face higher rent have an incentive to fundraise more – but unfortunately, this choice of instrument proved relatively weak in this sample. However, the charity's office expenses prove to be a stronger instrument. Office expenses include payments for office supplies, telephone services, equipment rental, bank fees, and costs related to postage and printing. The argument supporting the relevance of this instrument is identical to the argument made by *Andreoni and Payne* (2011) in favor of occupancy costs. Furthermore, office expenses should prove exogenous so long as they are not correlated with unobservable determinants of charitable contributions. It is possible that growth in an organization's assets may simultaneously bring about growth in both its office expenses and the contributions it receives. This would constitute a violation of the exclusion restriction. To address this problem, these specifications include a control for charities' assets, measured at the beginning of the charity's fiscal year.

The control function approach proceeds in two steps. The first step consists of estimation of Specification (2.13) via Poisson fixed-effects regression. The second step is to calculate $\hat{\nu}_{ist}$, the estimated residuals of Specification (2.13). This variable is normalized[8] and included in (H_{ist}, X_{ist}), the vector of controls in Specification (2.12), and can be understood as a sufficient statistic for the endogenous components of f_{ist}. Finally, standard errors are calculated via the bootstrap.

The system of equations (2.12)-(2.13) imperfectly divides the overall effect of food insecurity on private contributions into two mechanisms: a direct mechanism which operates independently of the charity's fundraising activities, and an indirect mechanism, capturing the extent to which food insecurity affects private contributions through fundraising. This division is imperfect because, even in the absence of measurement error, not all fundraising effort costs money. As illustrated in Figure 2.2, anti-hunger charities may change the content of their donor communications to incorporate

[8]The purpose of this normalization is to account for possible heterogeneity in the degree of endogeneity of the endogenous regressor. Endogeneity in this context arises from simultaneous causality: within one organization, both y_{ist} and f_{ist} may be correlated with the same time-varying unobservables. These time-varying unobservables may include, for example, the involvement of anti-hunger activists in the organization. For example, if Organization A reaches out to a potential donor who happens to be passionate about this cause, the resulting estimate of $\frac{\partial y}{\partial f}$ may be quite large. If Organization B only reaches out to apathetic potential donors, $\frac{\partial y}{\partial f}$ may prove much smaller than that of Organization A. By normalizing the sufficient statistic for endogeneity, heterogeneity of this form can be captured. See *Wooldridge* (2015) for further details.

current information about unmet need. These efforts would not be reflected in the dollar amount of fundraising expenses reported on the Form 990. If these non-financial aspects of fundraising play an important role in raising donors' awareness of food insecurity, the coefficient β_H will reflect the "direct" mechanism but also capture some of the "indirect" mechanism. Furthermore, since the variable f_{ist} is measured with error, and this variable is now included on the right-hand side of Equation (2.12), it follows that the resulting estimates will suffer from attenuation bias.

Figure 2.2: Communication with Donors via Fundraising Appeal

Source: *Food Gatherers* (2021)

2.4.3 Measurement Error

Charities may exercise some discretion in reporting each line item on the Form 990. This discretion is assumed to be limited to the way expenses may be allocated between fundraising, program spending, and other activities, as the other outcomes of interest are much more easily verifiable. Some activities may contain both a fundraising component and a program service component, and as a result, even an organization that is subject to a moderate degree of scrutiny could reasonably reallocate reported spending between categories. At the same time, charity watchdog groups incentivize organizations to underreport fundraising expenses. *Mayo* (2021) finds that organizations classified as Food charities by Charity Navigator relabel non-program service expenses as program service expenses in order to achieve an extra star under the Charity Navigator rating system. Not all organizations are eligible to be rated by Charity Navigator – in some cases, because the fundraising budget does not exceed 1% of total spending – but these charities may still face weaker versions of the same incentive.

The fundraising measure is therefore considered to contain some multiplicative measurement error, such that fundraising expenses appear artificially low. This measurement error will tend to inflate the variance of the estimates, but will not affect the consistency of the estimates so long as it is uncorrelated with other covariates (*Cameron and Trivedi* (1998)). As all specifications contain charity-level fixed effects, this assumption will hold so long as any deviations in the measurement error from its charity-specific mean are uncorrelated with within-state deviations in food insecurity or donors' income, or deviations in charities' assets from their charity-specific means.

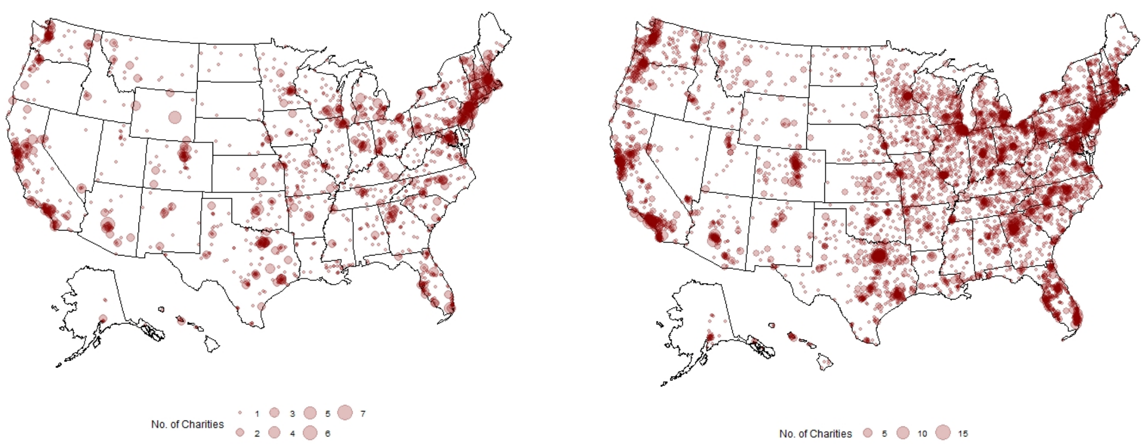
2.5 Data

This section describes the data compiled to estimate the specifications described in the previous section. First, charities dedicated to fighting food insecurity are identified using GuideStar's Philanthropy Classification System. Next, these organizations are matched to the financial data reported on their federal information returns. Finally, these charities are matched to state-level measures of hunger, income, and inequality.

2.5.1 Candid

This project uses data collected from Candid, a non-profit organization created by the 2019 merger of GuideStar and the Foundation Center (*McCambridge* (2019)). GuideStar is a directory of non-profit organizations. Its listings include all organizations exempt from taxation under Section 501(c) of the Internal Revenue Code, based on their appearance in the IRS' Business Master File of tax-exempt organizations and Publication 78, which lists all organizations eligible to receive tax-deductible charitable contributions. Newly exempt organizations may enter the database with a lag of up to six months. Organizations which are not required to apply for tax exemption, such as religious organizations, are only listed on GuideStar upon the organization's request.

Food aid organizations are identified using Candid's Philanthropy Classification System (PCS). This is a multi-dimensional taxonomy, which assigns organizations to at least one cause category. Recipient organizations can be matched to as many as five distinct cause categories. All GuideStar-listed organizations are classified according to the PCS at the point of their inclusion in the database, though some are classified as "Unknown or not classified". The set of charities listed as "food aid organizations" by GuideStar therefore includes all organizations for which provision of charitable food assistance constitutes one of its top five functions.[9]



(a) Form 990 E-Filers (b) All Organizations

Notes: The set of organizations depicted in Figure 2.3a reflects the estimation sample. Figure 2.3b includes these organizations, as well as Form 990-N filers, Form 990-EZ filers, and religious non-filers, which are identified as food aid organizations by Guidestar's Philanthropy Classification System.

Figure 2.3: Distribution of Food Aid Organizations, 2015

2.5.2 IRS Form 990

Organizations which claim tax exemption under Section 501(c)(3) of the Internal Revenue Code are required to file an annual information return, known as the Form 990. Organizations which hold over $500,000 in total assets at the end of the tax year, and which normally take in at least $50,000 in gross receipts, are required to file the full Form 990, which is the most detailed of these information returns. Until 2013, the IRS and the National Center for Charitable Statistics (NCCS) had digitized only a subset of fields from relatively small samples of Form 990 filings. These data

[9]This is PCS subject "Food aid", category SS030600.

limitations were effectively lifted for electronically filed forms beginning in 2011, when the IRS made the universe of Form 990 e-filings available to the public. This e-filing data contains many additional fields relative to the extracts previously published by the IRS or the NCCS, including a breakdown of organizations' contributions by source. In order to exploit this degree of detail, this analysis focuses on charities which file Form 990 in electronic format.

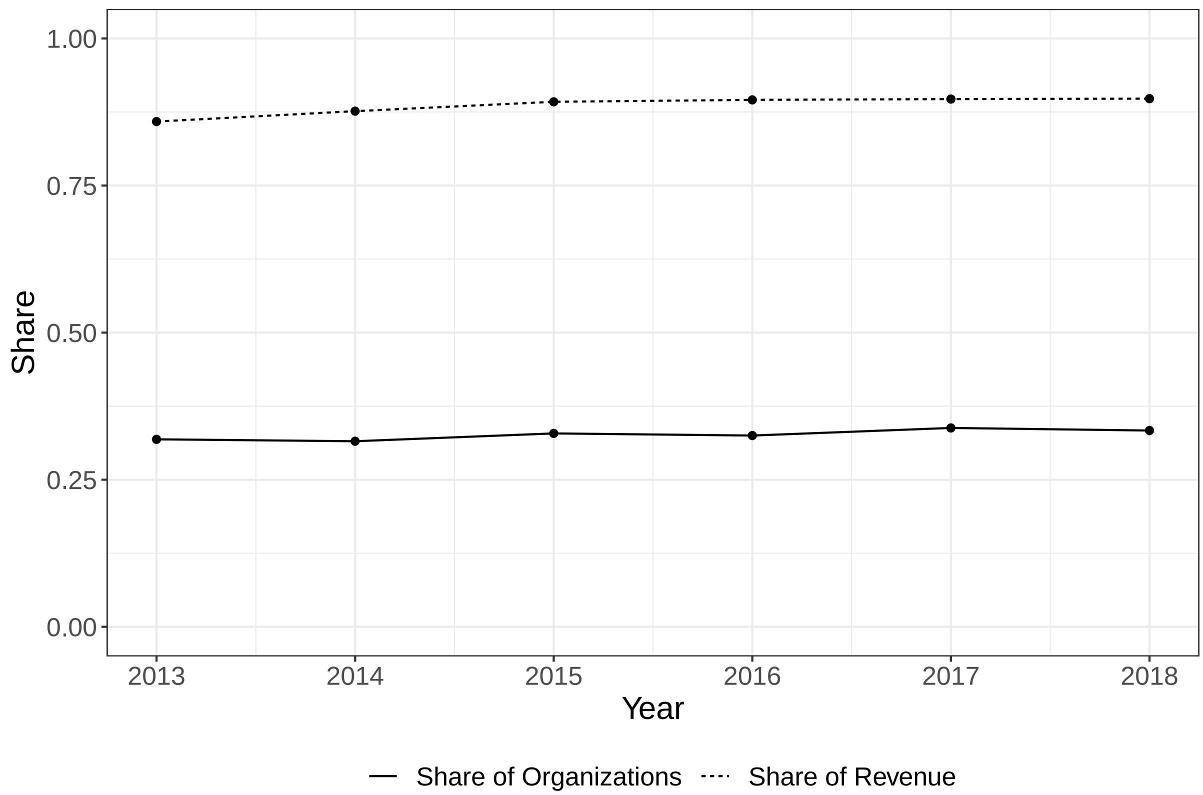


Figure 2.4: Share of Food Aid Organizations Represented in Sample

This sample restriction is not representative of the universe of 501(c)3 organizations, for two reasons. The first is that electronic filing has become more common since 2011, the first fiscal year for which data are available. The IRS will require Form 990 to be filed electronically for all fiscal years ending after July 31, 2020. As such, organizations which are observed for all seven years of the sample may be considered early adopters of a technology which eventually becomes compulsory. Secondly, the sample omits Form 990-EZ filers, due to differences in information reported between the two forms. *Marx* (2018) presents evidence that the relative complexity of Form 990 compared to Form 990-EZ induces charities to bunch at reporting thresholds. He finds that these charities manipulate their receipts by as much as $1,000 in order to avoid filing Form 990, but that the manipulation is concentrated among organizations which face filing the more complex form for the first time. Taken together, these data are clearly missing nonrandomly: the sample reflects larger, more technologically savvy organizations, and the smaller organizations represented in the sample have chosen to file a more onerous and costly form.

The IRS' Annual Extract of Tax-Exempt Organization Financial Data includes an indicator variable for electronic filing, which enables comparison between electronic and paper filers along several relevant dimensions. This comparison can be found in Appendix O. Electronic filers appear larger than paper filers in every way, although the selection attenuates in 2019, as the deadline for all organizations to convert to e-filing approaches. The lack of symmetry between electronic filers and paper filers confirms that the sample is nonrandomly selected. This selection may create some negative bias in the results if smaller charities are more responsive to food insecurity than larger charities, where "small" refers to the charity's level of assets, contributions, and/or expenses.

The resulting sample accounts for roughly 30% of all food aid organizations identified using the Candid's Philanthropy Classification System. However, since the organizations in this sample are, by definition, large compared to 990-N filers and 990-EZ filers, the sample used in the below analysis represents approximately 88% of gross revenue received by all food aid organizations.[10]

The Form 990 contributes data for a variety of charity-level outcome variables and covariates, for the years 2013 through 2018. These outcomes include fundraising expenses and private contributions.[11] Fundraising expenses include all expenses incurred to solicit both cash and in-kind contributions from public and private sources, including overhead expenses associated with fundraising.[12] Total private contributions is defined as total contributions less government grants and membership dues.[13] Importantly for food aid charities, these contributions must reflect the value of both cash and non-cash contributions, such as donated food. Private contributions may come from any source other than the government, including individual donors, foundations, or businesses. Other variables

[10] These figures omit revenue collected by organizations exempt from filing.

[11] In fiscal years 2013-2018, fundraising expenses are found in Part IX, line 25, column D. Total contributions are found in Part VIII, line 1h; total private contributions are defined as the difference between total contributions, government grants (found in Part VIII, line 1e), and membership dues (found in Part VIII, line 1b).

[12] Fees paid to professional fundraisers (Part IV, line 11e, column D) represent a strict subset of overall fundraising expenses.

[13] Government grants reflect all contributions to the nonprofit from the government for the primary benefit of the public, rather than the primary benefit of the governmental unit. This includes both grants and contracts.

sourced from the IRS Form 990 include total charitable assets at the beginning of the fiscal year[14] and total office expenses[15].

2.5.3 Food Insecurity

Unmet need for charitable nutrition assistance is measured using the food insecurity rate. Food insecurity is defined as "limited or uncertain availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways" (*Anderson* (1990)). The Current Population Survey Food Security Supplement (CPS-FSS), administered by the Census each December, asks an 18-question battery of all respondents in order to capture the degree of food security experienced at the household level. Households with children are considered to be experiencing food insecurity if they answer more than 3 of these questions in the affirmative, and experiencing very low food security if they answer at least 8 of these questions positively. For households without children, the relevant thresholds are 3 or 6 questions, respectively. As is standard practice in the charity literature, these data are matched to the Form 990 by the state in which the organization is headquartered. However, it is clear that charities' service area may be a subset of its overall state. Since the only estimates of food insecurity available below the state level are model-based imputations, the relevant measure of food insecurity for a particular charity is assumed to be the state-level rate for the states in which it operates.

Reliance on state-level measures of food insecurity will create a bias against finding a charitable response to hunger. To see why, note that in many cases, charities' service areas do not coincide with state borders. Anti-hunger charities may serve a particular metropolitan area, a particular county, or a particular region; all of these levels of geography may occur at the sub-state level. If, for example, a charity in the sample serves an urban population, but changes in the food insecurity rate are driven by that state's rural population, the charity may appear insensitive to these innovations in the food insecurity rate. This apparent null effect would obtain not because charities are actually insensitive to hunger, but rather because the measure of hunger employed is insufficiently relevant. However, while Form 990 data on anti-hunger charities provides information as to the set of states where a charity operates, it does not provide much insight into where this charity operates within a

[14]Part X, line 16, column A.
[15]Part IX, line 13, column A.

state. While the Form 990 can identify the county or metro area where a charity is headquartered, assuming that a charity only operates in this geographic area will result in estimates biased away from zero in the event that this assumption is wrong. As *Si* (2018) points out that proximity to a food bank is an important determinant of take-up, anti-hunger charities are assumed to operate only within the state's borders.

Food insecurity rates are measured as of the beginning of period t. This is accomplished by using a one-period lag of the food insecurity rate, noting that measures for period $t-1$ reflect food insecurity as of December of year $t-1$, and assuming that any difference between the food insecurity rate at the beginning of December and the food insecurity rate at the beginning of January is negligible.

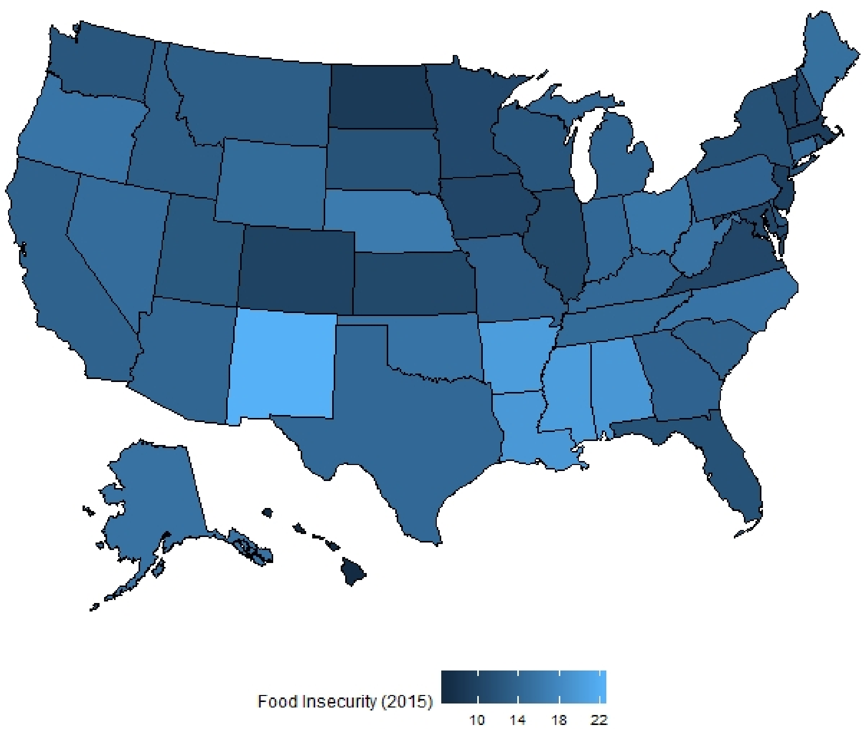


Figure 2.5: Food Insecurity Rates by State, 2015

2.5.4 Additional Covariates

As higher-income states have a greater capacity for generosity, it is useful to control for the income of the donor class in each state. Due to the high correlation between food insecurity rates and income among the poor, this measure will reflect the average income among the non-poor, defined as the households living above 500% of the federal poverty line. This variable is constructed based on data from the American Community Survey's one-year public use microdata sample. It is calculated by taking a weighted sum of household income by state and year, for the subset of respondents with an income-to-poverty ratio above 500%, and then dividing by the sum of the weights for this group. Tables produced using an alternative measure of income – personal income per capita – are presented in Appendix Q.

Per the model, inequalities between the donor and recipient classes will affect donors' generosity, as it may change the warm glow a donor derives from their gift. This dynamic is captured by including a control for state-level inequality: the Gini index. This variable, measured at the state-year level, is constructed using data from IPUMS-CPS.

Table 2.1: Summary Statistics

	Mean	St. Dev.	Min.	Median	Max.
Organization-Level Variables					
Fundraising Expenses	0.27	1.43	0.00	0.01	41.23
Private Contributions	8.04	68.88	0.00	0.57	2,621.02
Total Assets	6.89	74.24	0.00	0.91	2,713.57
Office Expenses	0.10	0.76	0.00	0.01	25.07
State-Level Variables					
Food Insecurity Rate (%)	14.11	3.07	6.36	13.74	25.22
Avg. Income > 500% of Poverty Line	0.16	0.01	0.13	0.16	0.20
Personal Income per Capita (Thousands)	0.05	0.01	0.03	0.05	0.08
Gini Index	0.48	0.04	0.39	0.48	0.61

Notes. The data includes 6,583 observations of 1,389 unique charities, observed between the years 2013 and 2018, inclusive. All financial variables measured in millions of constant 2015 dollars, unless otherwise specified.

2.6 Results

This section begins by presenting estimates of Equation (2.11). Next, it proceeds to decompose the private charitable response to food insecurity into two channels. The first, an "indirect" mechanism, reflects the extent to which this private charitable response is moderated by the charity's fundraising response to hunger. The second, a "direct" mechanism, reveals how donors would respond to changes in food insecurity if the charity had held fundraising constant. Finally, these results are interpreted in the context of the model presented in Section 2.3. Comparing the theoretical objects derived in Section 2.3 to the estimates presented in Section 2.6 yields some insight into the relationship between donors' generosity and local income inequality.

2.6.1 Food Insecurity Increases Charitable Fundraising

The results of this analysis begin in Table 2.2, which examines the mean effect of food insecurity on charities' outcomes. The first three columns take fundraising as the outcome variable, whereas the specifications which take private contributions as the outcome variable are presented in the second three columns.[16] When food insecurity rises by one percentage point, fundraising rises by 0.9%, on average. This estimate appears in Column 1 of Table 2.2. The estimates presented in Column 2 reveal that this relationship is robust to the inclusion of a control for state-level income inequality. Since fundraising increases in unmet need, Equation (2.10) implies that at least one of two conditions hold. It must be the case that either charitable fundraising is more effective when the charity's recipients are less well off, or that fundraising is less unattractive to the charity when their clients are in greater need. Per Column 3, rising income inequality appears to amplify charities' fundraising response to food insecurity. This indicates that the charity is indeed less hesitant to fundraise when society grows more unequal. While the estimates in Column 3 lack some precision, this may be due to the measurement error in the outcome variable, which will inflate the standard errors in a Poisson model.

On average, private contributions appear invariant to the food insecurity rate. The point estimates presented in both Columns 4 and 5 of 2.2 are positive, but quite close to zero and imprecisely estimated. While it may appear disheartening to observe that charitable contributions do not rise in food insecurity, neither do they fall. These estimates capture the total derivative of private contributions to food insecurity. Recall from Equation (2.7) that this total derivative is the sum of two channels. Food insecurity may affect private contributions either directly or indirectly, where the indirect channel operates through charitable fundraising. Since fundraising rises in food insecurity, and fundraising must generate private contributions in order to be a productive activity, it follows

[16] Note that fewer organizations are included in the specifications which take fundraising as an outcome variable. The Poisson pseudo-maximum likelihood estimation drops all organizations in which the outcome variable remains constant for the entirety of the sample period. This accounts for the discrepancy in organizations between Columns 1-3 and Columns 4-6 of Table 2.2.

that the indirect effect of food insecurity on private giving should be positive. For the total effect of food insecurity on private giving to be so close to zero, it may be the case that private giving would fall in food insecurity, were it not for the fundraising response. It follows that charities may spend more on fundraising in order to maintain their level of contributions, as unmet need rises. The next section verifies this prediction by decomposing the relationship between food insecurity and private giving into its two component channels.

Table 2.2: Average Effect of Food Insecurity on Charity Outcomes

	Fundraising			Private Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
Food Insecurity	0.009*	0.009*	-0.032	0.002	0.002	-0.062*
	(0.005)	(0.005)	(0.034)	(0.007)	(0.007)	(0.037)
Gini		0.218	-0.964		-0.364	-2.278*
		(0.424)	(1.006)		(0.748)	(1.288)
Food Insecurity × Gini			0.081			0.128*
			(0.071)			(0.075)
Log Avg. Inc. of Non-Poor	2.448*	2.485*	2.490*	2.939**	2.892**	2.906**
	(1.368)	(1.397)	(1.397)	(1.143)	(1.200)	(1.196)
Pseudo-R^2	0.663	0.663	0.663	0.948	0.948	0.948
No. Obs	5,029	5,029	5,029	6,583	6,583	6,583
No. Charities	1,071	1,071	1,071	1,389	1,389	1,389

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the organization level. All specifications include organization and year fixed effects. All financial variables measured in millions of constant 2015 dollars.

2.6.2 Fundraising Rises to Maintain Charitable Contributions

Table 2.2 clearly demonstrates that charities actively fundraise more when their clients' unmet needs rise. But what would happen to charitable contributions if these anti-hunger charities did not change their fundraising behavior? Per (2.7), after partialling out the effect of fundraising on private contributions, private contributions may fall in food insecurity. Estimates of coefficients in the system formed by equations (2.12) and (2.13), presented in Table 2.4, seek to verify this prediction.

The estimates for the first stage of this system (Equation (2.13)) are presented in Table 2.3. The inverse hyperbolic sine of office expenses is used as an instrument for charitable fundraising. While the weak instruments literature has yet to converge on an appropriate rule of thumb for assessing the strength of an instrument employed in a control function approach with a Poisson pseudo-maximum likelihood estimator used as the first stage, it is clear that this instrument exhibits a strong relationship to the endogenous regressor. Several variations on the first-stage specification are presented in Table 2.3, some of which include the state-level Gini coefficient and its interaction with the food insecurity rate. However, comparison of these three specifications reveals that the first stage regression with the best fit to the data is found in Column 1. Therefore, this is the first-stage equation used to estimate Equation (2.12).

The estimates of Equation (2.12) are presented in Table 2.4, which reports bias-corrected point estimates and confidence intervals.[17] These estimates reveal that, after controlling for fundraising expenses, charities which operate in states where food insecurity rises do not receive more private donations. In each column of Table 2.4, the point estimates of the direct effect of food insecurity on private contributions appear negative and very close to zero. While it is not possible to reject a one-sided null hypothesis that $\beta_H \geq 0$, the negative values predicted by the model and implied by the other estimates remain a possibility.

In interpreting these results, it is important to recall that the fundraising variable reflects only financial aspects of fundraising. Non-financial aspects of fundraising – such as unobservable changes to fundraising effort, or the content of donor appeals – are not captured by this variable. If increases in local food insecurity affect both unmeasured and measured dimensions of fundraising in the same direction, then this will create a positive bias in the estimates of β_H, the coefficient on food insecurity. As discussed in Section 2.4.2, this follows because food insecurity may affect private contributions through both a direct and an indirect channel. Measurement error in the fundraising variable, which mediates some of the effect of food insecurity on private contributions, will cause some portion of the "indirect" effect to be attributed to the "direct" channel instead. This implies that the coefficients on food insecurity in Table 2.4 are upper bounds for the true effect. This

[17] Note that only 990 organizations are included in Table 2.4, down from 1,389 organizations included in Table 2.2. Organizations which report zero fundraising expenses are omitted from estimation in Table 2.4.

provides additional support for the interpretation that the true "direct effect" of food insecurity on private contributions is negative, and therefore consistent with the model presented in Section 2.3.

By comparing these estimates with the model in Section 2.3, it is possible to gain some insight into donors' motivations. Recall that, per (2.5), the marginal return to an additional dollar of fundraising expenses will be positive if two conditions hold.

The first condition states that the marginal warm glow donors derive from their charitable giving grows stronger as perceived inequality rises. The second condition requires that either charitable fundraising must increase the salience of recipients' unmet need to donors, or donors must have some positive level of awareness of recipients' unmet need to begin with.

As the estimates of the elasticity of charitable giving to fundraising shown in Table 2.4 are consistently positive, both of these conditions appear to hold. The crucial condition to verify is the first condition, which is mathematically equivalent to $v_{12} > 0$. Note that if $v_{12} = 0$, and the marginal warm glow is unrelated to perceived inequality, then it would follow that $\frac{\partial G}{\partial F} = 0$; this is not the case. If, instead, $v_{12} < 0$, and the marginal warm glow diminishes with perceived inequality, the observed estimates could only obtain if charitable fundraising were to reduce donors' awareness of recipients' unmet needs. While it is possible that donors ignore information provided by the charity, as in Figure 2.2, it is implausible to suggest that these communications actually make donors less knowledgeable of recipients' circumstances. Therefore, while it is not possible to firmly conclude that salience increases in fundraising expenses, these estimates clearly indicate that donors derive greater warm-glow utility from giving in an environment of greater economic inequality.

If this is the case, then why would donors' gifts fall in food insecurity, if fundraising were held constant? Recall from Equation (2.6) that donors' gifts rise in recipients' resources if:

$$\left| -\frac{\sigma_2}{y_D}(Rtc^* - G + F) \right| > \left| \sigma R \frac{\partial tc*}{\partial y_R} \right| \tag{2.19}$$

Table 2.3: First Stage Specifications

	(1)	(2)	(3)
Food Insecurity	0.008*	0.008*	-0.021
	(0.005)	(0.004)	(0.028)
Gini		0.236	-0.606
		(0.459)	(0.888)
Food Insecurity × Gini			0.058
			(0.057)
IHS(Office Expenses)	0.235***	0.235***	0.234***
	(0.090)	(0.091)	(0.089)
Log Avg. Inc. of Non-Poor	1.922*	1.962*	1.969*
	(1.075)	(1.103)	(1.105)
Log Total Assets	0.188***	0.187***	0.187***
	(0.051)	(0.051)	(0.050)
Pseudo-R^2	0.663	0.663	0.663
No. Obs	5025	5025	5025
No. Charities	1071	1071	1071
χ^2 IHS(Office Expenses)	6.793	6.706	6.886
$p > \chi^2$	0.009	0.010	0.009
AIC	3260.769	3262.758	3264.717
BIC	3286.858	3295.369	3303.850

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the organizational level. All specifications include organization and year fixed effects. All financial variables measured in millions of constant 2015 dollars.

If an exogenous increase in food insecurity follows from a reduction in recipients' incomes, it will be accompanied by an increase in inequality. As inequality rises, the salience of recipients' unmet needs should fall; this is captured by the term on the left-hand side.[18] As recipients' incomes fall, takeup of food assistance should rise; this is captured by the term on the right-hand side. Per

[18]The estimates in Table 2.4 also confirm that the salience function must decrease in income inequality. To see this, note that the ratio of the coefficient on the log of fundraising to the coefficient on food insecurity must be negative, particularly given that the latter represents an upper bound for the true effect. Recall as well that while the model provides an expression for $\frac{\partial G}{\partial y_R}$, the coefficient β_H represented in Table 2.4 will instead be proportional to $-\frac{\partial G}{\partial y_R}$, as recipients' income is inversely related to food insecurity. Then the following must hold:

$$\beta_H \propto \sigma_2 \frac{(Rtc^* - G + F)}{y_D} - \sigma R \frac{\partial tc*}{\partial y_R}$$

Table 2.4: Direct and Indirect Effects of Food Insecurity on Contributions

	(1)	(2)	(3)	(4)	(5)	(6)
Log Fundraising	0.149	0.149	0.099	0.122	0.116	0.094
	[0.055, 0.459]	[0.054, 0.464]	[-0.001, 0.320]	[-0.005, 0.430]	[-0.007, 0.411]	[-0.032, 0.349]
Food Insecurity	-0.002	-0.002	-0.002	-0.002	-0.032	-0.026
	[-0.019, 0.008]	[-0.020, 0.008]	[-0.018, 0.009]	[-0.019, 0.009]	[-0.096, 0.038]	[-0.092, 0.042]
Gini		-0.436		-0.448	-1.324	-1.132
		[-2.032, 0.582]		[-1.999, 0.693]	[-4.083, 0.849]	[-4.190, 0.844]
Log Fundraising × Food Insecurity			0.003			0.003
			[-0.005, 0.008]			[-0.005, 0.008]
Log Fundraising × Gini				0.051	0.059	0.012
				[-0.189, 0.484]	[-0.179, 0.464]	[-0.212, 0.441]
Food Insecurity × Gini					0.060	0.048
					[-0.089, 0.191]	[-0.099, 0.181]
Log Avg. Inc. of Non-Poor	2.720	2.670	2.640	2.667	2.685	2.596
	[1.195, 5.153]	[1.046, 5.023]	[1.200, 5.155]	[1.055, 5.045]	[1.077, 5.019]	[1.086, 5.163]
Log Total Assets	0.075	0.075	0.071	0.074	0.074	0.070
	[-0.096, 0.175]	[-0.097, 0.173]	[-0.104, 0.170]	[-0.097, 0.173]	[-0.102, 0.175]	[-0.110, 0.175]
$\hat{\nu}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	[-0.020, -0.002]	[-0.020, -0.002]	[-0.020, -0.002]	[-0.020, -0.002]	[-0.020, -0.002]	[-0.020, -0.002]
No. Obs	4,397	4,397	4,397	4,397	4,397	4,397
No. Charities	990	990	990	990	990	990

Notes. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Bias-corrected point estimates and 95% confidence intervals (reported in brackets) are produced using 500 bootstrap replications. Bootstrap standard errors clustered at the organizational level. All specifications include organization and year fixed effects. All financial variables reported in millions of constant 2015 dollars. $\hat{\nu}$ represents the standardized, generalized residual of the first-stage specification, which is included in estimation of the structural equation as part of the control function approach. For further details, see *Wooldridge* (2015).

Table 2.4, donors' gifts fall in food insecurity, after holding fundraising constant. If these exogenous changes in food insecurity come from changes in recipients' resources, and if donors' incomes are held constant, then the model confirms that donors give less when recipients experience greater hardships. This counterintuitive result must obtain because the loss in salience generated by rising income inequality, weighted by the volume of unmet need, exceeds the salience-weighted increase in takeup of the charitable good. The same changes which exacerbate recipients' needs make it harder for donors to observe those needs, in the absence of an informational intervention from the charity.

2.7 Conclusion

When hunger rises, charities respond by increasing their fundraising. For each percentage point increase in the food insecurity rate, anti-hunger charities spend an additional 0.9% on fundraising. This pattern is consistent with a model in which charities are more willing to fundraise when their recipients' unmet needs rise. If charities were to hold fundraising constant in such a situation, donors to these organizations would not increase their generosity. On the contrary, estimates suggest that, after controlling for fundraising, a one-percentage-point increase in the food insecurity rate will reduce private contributions by at least 0.2%. This upper bound is statistically indistinguishable from zero, suggesting that in the most optimistic case, donors are completely unresponsive to changes in the food insecurity rate.

At first glance, this reaction to increased hunger among recipients seems quite ungenerous. However, these findings are consistent with the model presented in this paper. Based on *Duquette and Hargaden* (2021), this model rationalizes a disconnect in the emerging literature on the relationship between inequality and charity. The estimates imply that the marginal utility donors derive from giving is actually enhanced by social inequality. Why, then, is there such a disconnect between the enhanced "warm glow" donors receive from giving when recipients' unmet needs rise, and the reduction in their generosity observed in the same circumstance? This paper demonstrates that when inequality rises, donors become less aware of changes to recipients' unmet need. Without this awareness, donors derive less of a warm glow from supporting charities which provide their clients with essential social services, and therefore face less of an incentive to donate to these groups when

In this expression, the second term on the right-hand side must be weakly positive, as takeup of the charitable good falls in recipients' income. Then it must be the case that $\sigma_2 < 0$ and salience falls in income inequality.

their contributions are needed most.

These results underscore the importance of communication in forging links between donors and recipients. This link is crucial: if donors are not aware of changes in recipients' circumstances, then the private provision of charitable goods can become unreliable. This link is trivially present in previous models of voluntary public good provision, which assume that all donors to the charity also consume the goods and services this organization produces. In those models, exogenous reductions in the resources of non-contributors to the public good – which would bring about exogenous increases in unmet need – cannot affect the amount of voluntary public good provision. Only changes to contributors' resources, or the composition of the set of donors, can do that. This paper demonstrates empirically that when non-contributors' unmet need rises, contributors' gifts are affected, in an adverse way. Through fundraising – a form of communication – charities can mitigate this tendency, and thereby maintain their level of service provision.

Unfortunately, this communication can be costly for charities. So long as fundraising expenses are penalized by the key performance indicators used to evaluate nonprofits, charities which spend money to advocate to donors on their clients' behalf will appear less effective than organizations which do no such advocacy. As some causes generate more media attention than others, it may be the case that charities addressing some types of unmet need will find it necessary to spend money on advocacy more frequently than charities operating in other cause areas. Organizations which draw both donors and recipients from the same segment of the population are also less likely to face these challenges. When evaluating the performance of charitable providers of basic social services, overreliance on performance indicators which penalize fundraising may therefore cause donors to undervalue the benefit that these charities confer on their clients. Were it not for their additional fundraising, these organizations would have lost contributions, and each member of their growing clientele would receive a smaller slice of a shrinking pie.

CHAPTER III

Short-Run Effects of COVID-19 on the Nonprofit Sector

3.1 Introduction

The COVID-19 pandemic can be distinguished from previous natural disasters and recessions by its many unique characteristics. These characteristics make it difficult to predict its effect on the nonprofit sector. Not only did the pandemic affect individuals' ability to give, but it also hampered the delivery of charitable services, and in some cases, prevented operation entirely. At the same time, the pandemic prompted the government to provide additional support to businesses, including nonprofits. It is not clear whether the increase in public support would be enough to offset any negative changes in private contributions, or how the pandemic may have impacted nonprofit employment or program service expenditures. This paper is the first to use IRS Form 990 data to estimate the impact of the first year of the coronavirus pandemic on nonprofits.

Using a differences-in-differences framework, we leverage variation in the timing of charities' fiscal years to identify the effect of COVID-19 on the nonprofit sector at the beginning of the pandemic. If a nonprofit ends its fiscal year in December, January, or February, its fiscal year 2019 ended prior to the beginning of the COVID-19 pandemic in the United States. These charities make up our control group. Charities which end their fiscal year between March and November were exposed to the pandemic during fiscal year 2019; these organizations make up our treatment group.

We find that treated nonprofits received 20.2% fewer contributions from private donors, compared to control organizations, in fiscal year 2019 relative to fiscal year 2018. Employment at treated organizations fell by 13.7%, accompanied by a 40.6% reduction in the wage bill. These treated organizations also made 34.4% fewer program expenditures. These negative effects increased monotonically in the number of months a charity was exposed to the pandemic. While charities in the Health and Human Services sectors did not appear to lose private contributions due to the pandemic, both employment and program spending contracted substantially in these sectors. The Arts sector was particularly hard-hit by the pandemic; these organizations experienced particularly large declines in private contributions, employment, and program spending.

At the same time, government grants to charities exposed to the COVID-19 pandemic increased by a substantial 68.6%. This measure of public support does not reflect the impact of the Paycheck Protection Program, or PPP. Like the pandemic, this program began in March 2020, and was intended to help small employers retain their workforce. We estimate that 95% of treated organizations would have been eligible for the PPP program. To discover how the PPP may have affected the nonprofit sector, we match Small Business Association data on PPP loan recipients to IRS Form 990 data on nonprofits' finances. We are able to match 97,468 PPP loans to their recipients, and ultimately identify 23,388 unique Section 501(c)3 charities which receive PPP loans during fiscal year 2019.

We find that PPP loans cushioned the blow of the pandemic, both for eligible organizations and for those which became early adopters of the PPP. Employment at PPP-eligible charities increased by 12.1% relative to PPP-ineligible charities; and employment at eligible charities which took up PPP in fiscal year 2019 increased by 18.7% relative to those which did not take up PPP right away. We also find that, while government grants increased for all COVID-exposed charities in fiscal year 2019, the government directed relatively more of its non-PPP financial support to benefit charities which were ineligible for the program. Additional results suggest that PPP recipients used both types of government funding to maintain their workforce, but were much more likely to fund program expenditures out of government grants than out of PPP loan funding.

This work contributes to our understanding of the effect of macroeconomic shocks on the nonprofit sector. Previous work has shown that this sector is sensitive both to economic calamities and to natural disasters. *Meer et al.* (2017) find that donations fell on both the extensive and intensive margin during the Great Recession, with changing attitudes to giving and increased uncertainty explaining much of the decline. *Reich and Wimer* (2012) also document steep reductions in giving during the Great Recession, but find that funding to food banks in fact rose by 32% between 2008 and 2009. Using stock market data, *List and Peysakhovich* (2011) highlight the asymmetric impact of booms and busts, with giving more responsive to stock market upturns than downturns. Finally, a recent paper by *Deryugina, Tatyana and Marx, Benjamin M* (2021) finds that donations in response to deadly tornadoes do not come at the expense of other charities, implying that giving need not be in fixed supply.

Early survey evidence on the effect of the pandemic on the nonprofit sector has been mixed. In April 2020, a survey designed by Charity Navigator and Reuters suggested that the pandemic had a huge impact on charity finances and service delivery. 50% of the 295 survey respondents said that they had experienced increased demand as a result of the pandemic, and yet 64% had had to cut back on program services. Further, 27% had or expected to layoff workers, while 13% planned to increase their workforce. These results were corroborated by the Center for Effective Philanthropy's Persevering through Crisis survey, conducted in February 2021. As in the Charity Navigator/Reuters survey conducted a year earlier, half of these respondents reported increased demand, and roughly 30% reported having laid off or furloughed workers. 58% of these 163 participants reported they had reduced service provision, while 88% reported that they had meaningfully altered the services provided. According to a Harris Poll, 1 in 5 American households report that they have donated less since the start of the pandemic. However, of the survey respondents who said that they are still giving, more than half say that they are giving the same amount, and 21% say they are giving more. Indeed, new data from the Fundraising Effectiveness Project suggests that the universal charitable deduction introduced by the CARES Act led to a surge in donations in November and December 2020. Based on information from 2,496 nonprofits, the study finds that giving grew by 10.6% in 2020, yet donor retention fell by 4.1%.

Experimental work conducted in England suggests that online fundraising appeals which mention COVID-19 increase donations, especially in areas with more cases and greater media coverage of the pandemic (*Adena, Maja and Harke, Julian* (2022)). Qualitative studies have identified the pandemic as a crisis for nonprofit workplaces, in particular (*Kuenzi et al.* (2021)). While some studies have begun to describe the quantitative impact of the pandemic on particular geographic regions (*Grønbjerg et al.* (2021)), more work is needed to identify the causal impact of exposure to COVID-19 on the nonprofit sector in the United States as a whole. To our knowledge, we are the first to use Form 990 data to examine the impact of the pandemic on the U.S. nonprofit sector.

We also contribute to the literature evaluating the Paycheck Protection Program, by highlighting its impact on relatively large 501(c)3 charities. Our estimates imply that PPP eligibility prevented the loss of 5.25 jobs per eligible organization, on average. Among eligible organizations, early take-up of a PPP loan prevented the loss of 13.72 jobs, on average. This translates into 465,398 nonprofit jobs saved due to PPP eligibility, and nonprofit 286,478 jobs saved due to early take-up. These figures are consistent with previous work on the impact of PPP on employment (e.g. *Chetty et al.* (2022), *Autor et al.* (2022), *Granja et al.* (2022)): estimates of the number of jobs saved in the first year of this program range from 1.4 million to 2.02 million jobs. Using these previous estimates as a reference point, our estimates imply that between 23% and 33% of jobs saved by the Paycheck Protection Program were located in the nonprofit sector. As nonprofit employees make up roughly 10% of the U.S. labor force, these estimates suggest that the nonprofit sector benefited disproportionately from the Paycheck Protection Program.

The rest of the paper is outlined as follows: Section 3.2 describes the data and Section 3.3 outlines our empirical approach. Section 3.4 presents the headline results, while Section 3.5 presents heterogeneity analyses and a robustness check. Section 3.6 concludes.

3.2 Data

This project relies on information found in the IRS Form 990, matched to data on Paycheck Protection Act loans made to nonprofits.

3.2.1 IRS Form 990

All IRS Section 501(c)(3) organizations[1] with gross receipts of over $50,000 are required to file an annual information return with the IRS[2]. Failure to file for three consecutive years results in the automatic revocation of an organization's tax-exempt status. Nonprofits with gross receipts of over $200,000 are required to file a Form 990, while those with receipts between $50,000 and $200,000

[1] 501(c)(3) nonprofits are those whose mission relates to charity, education, science or public safety testing.

[2] Churches and other houses of worship, and governmental organizations such as public universities are not required to file.

can file either a 990 or a 990-EZ[3]. These information returns contain detailed information on a charity's financials, as well as personnel and program service activities.

We focus on the set of nonprofits that e-file the Form 990[4]. The reason for this is that paper forms are processed with a lag, while e-filings are available immediately. With a few exceptions[5], e-filing is accessible to all organizations that file a Form 990, and required for those with net assets greater than $10 million[6]. Focusing on the set of e-filers means that we are likely excluding smaller, less sophisticated organizations. However, these are a very heterogeneous group, and so it is hard to know how they would have been affected by the pandemic[7].

Our main variables of interest are private contributions[8], government grants, the number of employees[9], salaries, and program service expenses.[10] Private donations may come from individuals, estates, corporations, and/or other nonprofit organizations, while government grants include grants received from all levels of government, excluding reimbursements for services provided by the nonprofit under a government contract[11]. Loans made to nonprofits under the Paycheck Protection Program are recorded as government grants in the fiscal year in which they were forgiven.

The final sample excludes organizations with negative values of total contributions, government grants, assets, revenue, expenses, program spending, fundraising, and salaries, as well as organizations for which reported government grants exceeds total reported contributions. It also excludes all charities which file Form 990s reflecting "short" fiscal years, covering periods of less than 12 months. Finally, any Form 990 filers which are not tax-exempt under Section 501(c)3 are dropped

[3]Private foundations file a 990-PF.

[4]Charities that e-file are roughly twice as large as those that paper file. The difference is statistically significant across a range of variables (e.g. contributions, assets, revenue and number of employees).

[5]These include name change returns, returns from organizations with an exempt status application still pending, and returns older than the two prior years. Importantly, they also include short-year returns, which occur when an organization changes its accounting period. This allows us to identify and drop observations in which the charity files a short-year return.

[6]Private foundations and charitable trusts are also required to e-file if they file at least 250 returns annually, regardless of asset size.

[7]Less sophisticated organizations may be less adaptable, making it harder to survive, while smaller organizations may have particularly loyal donors and volunteers, which would make it easier.

[8]This is defined as total current contributions less government grants, which are examined separately.

[9]This includes paid employees only, not volunteers.

[10]Estimates of the effect of COVID-19 on two additional outcomes, fundraising expenses and total revenue, are presented in Appendix R. Fundraising includes expenditures associated with fundraising events, professional fundraising fees, and costs to apply for grants from both private and public sources. Professional fundraising fees are payments made to external organizations for conducting fundraising or for consulting on fundraising.

[11]These types of payments are reported as program service revenue.

from the sample.

3.2.2 PPP Loan Data

Many nonprofit organizations received fully guaranteed loans from the federal government through the Paycheck Protection Program (PPP). This program began on March 27, 2020, and ran through May 31, 2021, as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act. Nonprofits were eligible for PPP if they were sufficiently small employers: they must either have employed no more than 500 employees, or have met the Small Business Association's size standard for the nonprofit's primary industry (*Office of Inspector General of the U. S. Small Business Administration* (2022)). Data on PPP loan recipiency comes from the U.S. Small Business Administration[12]. This dataset includes the universe of PPP loans. It includes the name and address of the borrowing organization, an indicator for the organization's nonprofit status, and characteristics of the loan. These loan characteristics include the amount and dates of loan approval and forgiveness, as well as the term of the loan.

Organizations identified by the SBA as holding nonprofit status are matched to the set of charities in the IRS Form 990 electronic filings. As the e-filing data represent the largest charities in terms of assets and revenue, and the PPP loans were extended to relatively small nonprofits in terms of the number of workers, the overlap between these two datasets is imperfect. We proceed to match Form 990 e-filers to their PPP loans using the organization's name and address. First, candidate matches are identified by comparing organizations' names in the PPP and Form 990 data. For each loan recipient represented in the PPP data, a candidate match from the Form 990 data is the organization with the most similar name, measured using the Jaro-Winkler distance metric. Once candidate matches are returned, the match quality is verified in several ways. First, candidate matches are discarded if the loan recipient and its candidate match are located in different states. Second, the loan recipient's five-digit zip code, city name, and street name are compared to that of its candidate match. Exact matches are identified if the loan recipient's name and address are identical to that of the candidate match. Inexact, but acceptable, matches are identified if the Jaro-Winkler distance between the loan recipient's name and that of its candidate match is less

[12] `https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program/ppp-data`

than 0.18, the cosine distance between the loan recipient's street address and that of its candidate match is less than 0.3, and the distance between the zip codes reported by the loan recipient and its candidate match is less than 2 miles. Exceptions are made in the case where an organization lists a P.O. Box as its address for purposes of either loan recipiency or Form 990 filing; in this case, the zip code distance and address similarity restrictions are relaxed.

We are able to match 97,468 unique loans to 70,677 unique Form 990 e-filers which received loans under the Paycheck Protection Program. Of these loans, only 18 were forgiven during the recipient's 2019 fiscal year.[13] The Small Business Administration's PPP dataset includes a total of 271,513 loans made to nonprofits. 76,732 of these loans are made to religious congregations, which are not required to file any version of the Form 990[14]. After removing religious non-filers, which cannot be matched to Form 990 data, 194,781 loans remain. Our procedure successfully matches 50% of these loans to the recipient's Form 990 filings. As Form 990 filers are relatively large, and PPP loans were aimed at smaller firms, it is likely that the recipients of the remaining 50% of loans file either the Form 990-EZ or the Form 990-N.

Of these 70,677 Form 990 e-filers, only 58,973 were Section 501(c)3 charities; the remaining 11,704 were tax-exempt under different subsections of Section 501(c), and so were excluded from analysis. A further 35,585 Section 501(c)3 charities received approval for a PPP loan at some point after their 2019 fiscal year. As treatment takes place after our sample period, these organizations were dropped from the analysis. However, we are able to identify 23,388 501(c)3 charities which had a PPP loan approved during its 2019 fiscal year. After the remaining sample restrictions are imposed, we are left with 20,872 charities which received PPP loans in fiscal year 2019.

[13]From the 2020 IRS Form 990 instructions: "Amounts of PPP loans that are forgiven may be reported on line 1e as contributions from a governmental unit in the tax year that the amounts are forgiven." Therefore, the measure of government grants observed during fiscal year 2019 does not reflect PPP loan recipiency, for all but the 18 organizations which had loans forgiven during this period.

[14]76,732 total loans are made to organizations which contain the words "church," "congregation," "assembly of God," "temple," or "mosque" in their names.

Table 3.1: Balance Table: PPP Eligibility and Take-Up

	Ineligible		Eligible		No Loan Approval		Any Loan Approval	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Private Contributions	14,172.11	78,390.48	1,351.47	35,624.50	1,347.56	40,469.19	1,364.13	8,546.55
Government Grants	15,593.83	126,558.28	775.40	8,033.96	747.40	8,987.05	866.24	3,449.77
Employment	2.09	5.16	0.04	0.08	0.03	0.07	0.07	0.09
Salaries	99,055.58	267,144.53	1,619.33	8,240.04	1,459.38	9,182.67	2,138.29	3,776.56
Program Services	175,773.27	475,806.53	3,831.71	35,867.85	3,876.41	40,601.07	3,686.67	10,591.22
State Population	12,876.49	10,783.50	13,503.04	11,765.37	13,684.19	11,816.40	12,915.33	11,579.03
Charity Assets	401,485.22	1,795,429.00	10,646.10	155,607.86	11,598.96	176,960.52	7,554.55	34,086.05
Arts Charity	0.03	0.17	0.10	0.30	0.09	0.29	0.13	0.34
Education Charity	0.29	0.45	0.24	0.42	0.23	0.42	0.25	0.43
Health Charity	0.39	0.49	0.13	0.34	0.13	0.34	0.13	0.34
Human Services Charity	0.25	0.43	0.35	0.48	0.36	0.48	0.34	0.47
Other Charity	0.04	0.19	0.18	0.38	0.18	0.39	0.15	0.36
Observations	4050		88591		67719		20872	

Notes. All figures in thousands.
Each variable is an average that reflects fiscal year 2018, which preceded the pandemic.
Statistics for organizations with and without loan approvals exclude PPP-ineligible charities.

PPP eligibility is very common in the sample. Organizations are considered eligible to apply for a PPP loan if they reported employing no more than 500 people at the end of fiscal year 2018, and if the PPP program began during their 2019 fiscal year. Using this criterion, 95.7% of charities in the sample appear eligible for PPP. This is an imperfect proxy for eligibility. To see why, consider an organization which ends its fiscal year in June. Such an organization might have employed 501 individuals at the end of its 2018 fiscal year, which occurred in June 2019. By the time the CARES act was enacted in March 2020, this firm may have lost two employees. This proxy would then make this charity appear ineligible for PPP, when in fact this was not the case. It is reassuring to note that no ineligible charities appear to take up a PPP loan. 26.8% of eligible charities have a PPP loan approved or forgiven during fiscal year 2019. Among charities which take up PPP, the average loan amount approved during fiscal year 2019 is $410,800. Loan sizes are quite variable in the sample: the standard deviation of the loan amount is $686,480.

3.3 Empirical Strategy

Our primary source of identification comes from variation in charities' fiscal years. Roughly 60% of charities' fiscal years coincide with the calendar year, and most have either June or December fiscal year ends. However, for charities which end the fiscal year in any month between March and November of 2020, the Form 990 filing for the 2019 fiscal year will reflect some degree of exposure to the COVID-19 pandemic. For example, an organization with a fiscal year ending in April will file a 2019 return covering the period from May 2019 through April 2020. If the beginning of the coronavirus pandemic in the United States is considered to be March 15, 2020[15], then this organization's 2019 Form 990 reflects 1.5 months of exposure to the pandemic. By contrast, US-based organizations with fiscal years ending in December, January, or February should be minimally affected by the pandemic, if at all. Figure 3.1 illustrates the variation we exploit. For the same fiscal year (2019), organizations that file in June are exposed to COVID-19, while those that file in December are not. In this way, the first difference compares fiscal year 2018 with fiscal year 2019, and the second difference compares organizations with fiscal years ending in December 2019 through February 2020, to those with fiscal years ending March - November 2020. The identifying

[15]On this date, the CDC first issued recommendations against gatherings of 50 or more people, and the Federal Reserve cut the federal funds target rate.

assumption we require is that the difference between charities that filed before and after the onset of COVID-19 is constant over time.

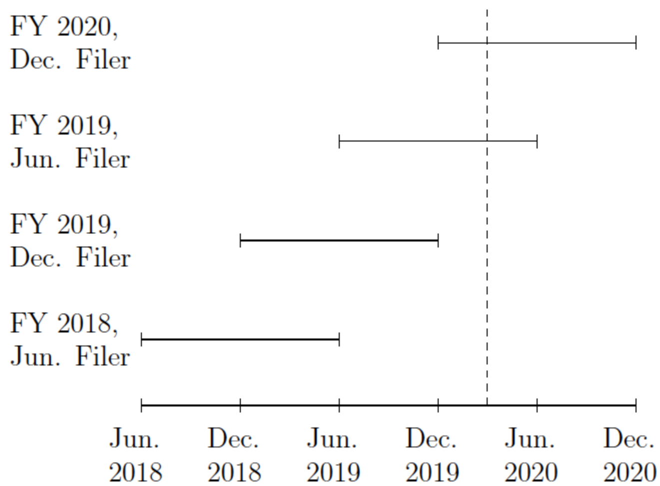


Figure 3.1: Variation in Fiscal Year

With March-November filers serving as our treatment group, and December-February filers our control group, the main specification is defined as follows:

$$Y_{it} = \beta^{post}\mathbf{1}(FilingMonth_i >= March) \cdot After_{it} + \alpha^{post}\mathbf{1}(FilingMonth_i >= March) + \gamma After_{it} + \varepsilon_{it} \tag{3.1}$$

where i indexes charities and t indexes fiscal year (2019 or 2020). The first treatment group is represented by the indicator variable $\mathbf{1}(FilingMonth_i >= March)$, which captures the assignment of March-November filers to a treatment group and December-February filers to a control group. $After_{ist}$ is a dummy variable that takes the value 1 for fiscal year 2019 and 0 for fiscal year 2018[16]. β^{post} is our coefficient of interest, and measures the effect of COVID-19 on charities that filed after the onset (any time from March onwards). Our outcomes of interest, Y_{it}, are transformed using an inverse hyperbolic sine function[17], and standard errors are clustered at the state level.

We control for assets, sector, and state of filing in the results reported in Appendix Table T.1.

[16]Fiscal year x includes all filing year end dates between December x and November $x+1$.

[17]The inverse hyperbolic sine function, $y = \ln(x + \sqrt{x^2+1})$, is an approximation of the natural log which allows for retention of zeroes. As such, the interpretation of coefficients from inverse hyperbolic sine - linear models is an approximate semi-elasticity, and the interpretation of coefficients from inverse hyperbolic sine - inverse hyperbolic sine models is an approximate elasticity.

However, the decision to omit any controls in the main specification is influenced by the work of *Sant'Anna and Zhao* (2020). The authors find that including covariates in a difference-in-difference specification only produces unbiased estimates if treatment effects are homogeneous in the covariate, or if covariate-specific trends are equal between treatment and control groups. The assumption of homogeneous treatment effects is likely violated in our setting. Charities filing in states that were harder hit by COVID-19 were likely differentially affected. And, as one might expect health-oriented charities to be differentially affected by a global pandemic than charities in other sectors, we do not expect treatment effects to be homogeneous across sectors either. Finally, if assets are considered to be a measure of charity size, this is also an inappropriate control, as small charities may also have been affected differently from large charities. Organizations of different sizes may have had different degrees of success attracting or retaining donations. Larger charities may have had an easier time avoiding layoffs than smaller charities, but may have borne larger costs associated with the cancellation of in-person fundraisers. We therefore exclude covariates in the main specification.

After estimating a version of Equation 3.1, which pools observations over time and across sectors, we explore heterogeneity by filing month and sector (Appendix S details heterogeneity by COVID-19 intensity). For the latter, we estimate five specifications using only filings from organizations belonging to the NTEE sector $k \in \{\text{Arts, Education, Health, Human Services, Other}\}$. The IRS uses the NTEE to classify tax-exempt organizations according to subject area. This system has its limitations: in particular, charities are often misclassified into particular sub-sectors (*Fyall and Gugerty* (2018)). However, by using the broadest possible categorization of charities into sectors, we are able to glean useful information about the heterogeneity of the effect of COVID-19 according to the type of services charities provide, while avoiding most possible misclassification errors.

As such, we estimate the impact of the pandemic along several different dimensions. The first specification is a simple difference-in-difference model, comparing charities that filed after the onset of COVID-19 with those that did not. The second disaggregates this impact to the monthly-level, allowing for heterogeneous treatment effects based on organizations' degree of exposure to the virus. The third specification compares the impact of COVID-19 across broad sectors.

3.3.1 Month-by-month

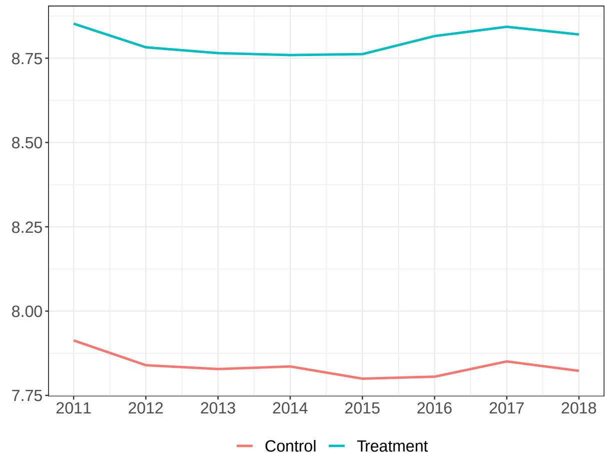
In order to trace out the month-by-month impact of the pandemic, Equation 3.1 is estimated separately for each filing month:

$$Y_{imt} = \beta_m^{post}\mathbf{1}(FilingMonth_i = m) \cdot After_{it} + \alpha_m^{post}\mathbf{1}(FilingMonth_i = m) + \gamma After_{it} + \varepsilon_{imt} \quad (3.2)$$

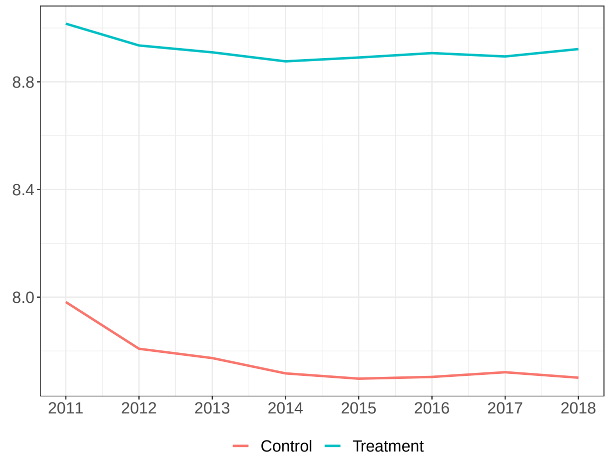
where $m = \{\text{March, ... , November}\}$. For each of these specifications, the treatment group defined by having a fiscal year end in month m is compared to the same control group used for the specifications described in Section 3.3. Y_{imt} are again transformed using an inverse hyperbolic sine function, and β_m^{post} captures the effect of COVID-19 on charities that filed in month m, where those charities that filed later were exposed to the pandemic for longer. Standard errors are clustered at the state level.

3.3.2 Identification assumptions

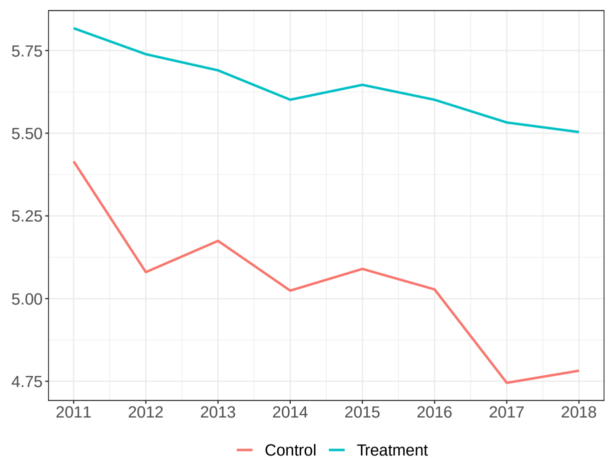
Before presenting the results, it is important to understand what is required for identification. This empirical strategy requires that the difference between charities filing before and after the onset of COVID-19 is constant over time. While each specification focuses on a different subset of these charities, based on sector or filing month, we present pre-trends which take the average across all charities for which the filing year ends between December and February, and compare it to the average across all charities for which the filing year ends between March and November. Figure 3.2 displays these pre-trends for the period 2011-2018 for the inverse hyperbolic sine of each of our outcomes of interest. There is clearly a level difference in each of the outcomes, but the similarity in trends between the treatment and control groups supports the difference-in-difference identification assumption.



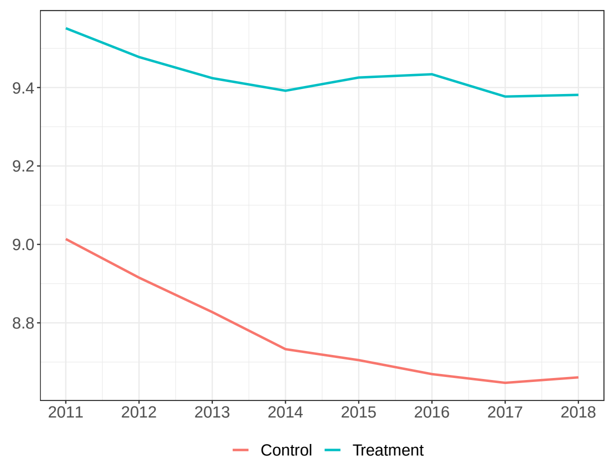
(a) Private Contributions



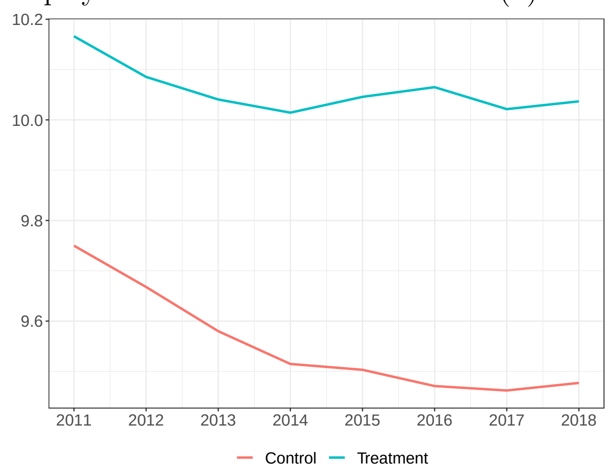
(b) Government Grants



(c) Total Employees



(d) Total Salaries



(e) Program Service Expenses

Figure 3.2: Pre-Trends

Notes. Dependent variables are transformed via the inverse hyperbolic sine function. All dollar figures in thousands of constant 2015 dollars. Years presented on the x-axis.

Although the parallel trends assumption permits level-differences, it is still helpful to understand how charities with fiscal year ends pre- and post-COVID differ. Table 3.2 reports these differences, showing that in every dimension, March to November filers are significantly larger than December to February filers. These level differences occur because larger charities are more likely to experience a greater degree of volatility in revenues towards the end of the calendar year. Furthermore, many of them receive grants for which the grant cycle does not end in December. These annual cash flow patterns, which grow more pronounced with charity size, create incentives for larger charities to choose fiscal year ends which do not coincide with the end of the calendar year. To that end, it may be useful to bear in mind that the source of variation we exploit – the ending month of the fiscal year – is not exogenous, but rather is pre-determined. As charities were no more able to predict the onset of a global pandemic than any other social entity, it is reasonable to rule out the possibility that charities chose their fiscal year ends in order to select some other level of treatment in this context. We therefore consider this pre-determined source of variation to be as good as exogenous.

Table 3.2: Balance Table

	Dec.-Feb. Filers		Mar.-Nov. Filers	
	Mean	St. Dev.	Mean	St. Dev.
Private Contributions	739.99	8,794.77	1,910.80	38,575.25
Government Grants	218.91	2,100.39	1,422.29	27,756.52
Employment	0.04	1.06	0.13	1.16
Salaries	1,017.45	18,387.20	5,875.08	59,821.17
Program Services	2,112.72	35,617.24	11,341.35	111,142.41
State Population	13,331.97	11,326.89	13,477.31	11,725.35
Charity Assets	4,841.32	67,799.05	27,716.34	412,693.59
Arts Charity	0.09	0.28	0.10	0.30
Education Charity	0.09	0.29	0.24	0.43
Health Charity	0.13	0.33	0.14	0.35
Human Services Charity	0.38	0.49	0.35	0.48
Other Charity	0.31	0.46	0.17	0.38
PPP-Eligible	0.99	0.10	0.96	0.20
PPP Take-Up	0.00	0.00	0.23	0.42
Observations	81110		123733	

Notes. All figures in thousands.
Each variable is an average that reflects fiscal year 2018, which preceded the pandemic.

Finally, in order to give a causal interpretation to our results, we must rule out any potential confounders. While the COVID-19 pandemic was one of the defining features of the year 2020, the presidential election remains the single largest potential confounder to occur during our treatment period. Section 3.5.3 presents the results of a triple difference regression, with the third difference comparing charities' outcomes in the run-up to the 2020 presidential election to their outcomes in the years leading to the 2016 presidential election. The George Floyd protests that began in May 2020 were another event that took place following the onset of the pandemic, and could have impacted the treatment and control groups differentially. However, these events primarily affected a small subset of civil rights charities, and not overall patterns of giving or service delivery.[18] Furthermore, some argue that the COVID-19 pandemic helped to fuel these protests. *Arora* (2020) finds that people who experienced negative financial consequences because of the pandemic were much more likely to join a protest. These protests' unprecedented size and scope can therefore be understood as a product of the pandemic, although the inciting incident was not. Therefore, these events can be viewed as a mechanism through which the pandemic affected charities, rather than as a confounder.

3.3.3 Identifying the Effect of PPP

As only 18 PPP loans were forgiven during any organization's fiscal year 2019, very few organizations in the sample would have reported these loans on their Form 990. Nevertheless, the possibility of using PPP funds, either during the current fiscal year or in the future, may have encouraged eligible organizations to retain staff or spend more on mission-related programming. The following specification captures the effect of PPP eligibility on charities:

$$Y_{it} = \gamma_1 \mathbf{1}(Eligible_i) \cdot After_{it} + \gamma_2 \mathbf{1}(Eligible_i) + \gamma_3 After_{it} + \nu_{it} \tag{3.3}$$

Here, $\mathbf{1}(Eligible_i)$ is an indicator variable, taking the value 1 if a charity had no more than 500 employees at the end of fiscal year 2018, and 0 otherwise. As the PPP program began in March 2020, Form 990 filers which end their fiscal year in December through February would not have had the opportunity to take up this program in fiscal year 2019, even if they were small enough

[18]Table T.6 presents results for civil rights organizations separately, and compares them to results for all charities excluding civil rights organizations. Wald tests for differences in treatment effects between civil rights and non-civil rights organizations are unable to reject the null hypothesis that these groups of organizations responded to the pandemic in the same way.

employers. By contrast, all charities which were exposed to the pandemic could have benefited from PPP, if they employed sufficiently few people. This specification is therefore estimated using a subsample of March through November filers only.

As discussed above, only about one-quarter of eligible charities had a PPP loan approved during fiscal year 2019. The following two specifications provide insight into how take-up of these loans may have impacted charitable contributions, employment, and program spending:

$$Y_{it} = \delta_1 \mathbf{1}(TakeUp_i) \cdot After_{it} + \delta_2 \mathbf{1}(TakeUp_i) + \delta_3 After_{it} + \eta^1_{it} \quad (3.4)$$

$$Y_{it} = \theta_1 IHS(ApprovalAmount)_{it} + \theta_2 \mathbf{1}(TakeUp_i) + \theta_3 After_{it} + \eta^2_{it} \quad (3.5)$$

Here, $\mathbf{1}(TakeUp_i)$ takes the value of 1 if an organization chooses to take up PPP in fiscal year 2019. To the extent that this variable captures organization-level, time-invariant unobservables which would lead a charity to become an early adopter of this program, δ_1 should capture the effect of extensive-margin PPP take-up on charity outcomes, Y_{it}. However, there may very well be time-varying unobservables which influence an organization's propensity to apply for PPP early, or at all; and so this parameter should be interpreted with caution. Similarly, $IHS(ApprovalAmount)_{it}$ reflects the inverse hyperbolic sine of the loan amount a charity received during fiscal year 2019, and so θ_1 reflects the relationship between intensive-margin take-up of PPP and charity outcomes. These specifications are estimated on a subsample of organizations which were eligible for PPP.

3.3.3.1 Nonprofits' Reliance on Government Grants and PPP

As discussed above, PPP loans represent a distinct source of funds from government grants for organizations in this sample. As PPP loans were intended to serve a particular purpose – to help small businesses maintain their workforces during a public health emergency – it is possible that nonprofits used these two sources of funds to serve different purposes.

Following Duquette (2017), we estimate the relationship between charity outcomes and revenue sources using a first-differences model:

$$\Delta Y_{it} = \beta_g \Delta IHS(GovGrants)_{it} + \beta_p \Delta IHS(ApprovalAmount)_{it} + \eta_{it} \quad (3.6)$$

This specification will be estimated on the subsample of PPP recipients. Tests of the null hypothesis $\beta_g = \beta_p$ will shed light on how these nonprofits viewed different streams of government support during the pandemic.

3.4 Results

Table 3.3 presents the results of our main specification (Equation 3.1) for each outcome: private contributions, government grants, employment, total wage bill, and program service expenses. The impact of COVID-19 on fundraising expenditures and total revenue is presented in Appendix R. The coefficients on "Any Exposure · After" correspond to the coefficients of interest, β^{post}. Outcomes are grouped into three categories for the discussion that follows: public and private contributions, labor market outcomes, and program service spending.

Table 3.3: Impact of COVID-19 on Charity Outcomes

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
Any Exposure · After	-0.202***	0.686***	-0.137***	-0.406***	-0.344***
	(0.036)	(0.067)	(0.017)	(0.041)	(0.026)
Any Exposure	0.042	2.023***	0.973***	2.199***	1.347***
	(0.065)	(0.176)	(0.045)	(0.123)	(0.046)
After	0.194***	-0.067	0.083***	0.312***	0.219***
	(0.022)	(0.046)	(0.013)	(0.035)	(0.022)
Constant	10.309***	3.079***	1.737***	8.311***	12.667***
	(0.077)	(0.187)	(0.045)	(0.117)	(0.048)
Observations	341758	341758	341758	341758	341758
R^2	0.000	0.037	0.040	0.023	0.037

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function.

3.4.1 Public and Private Contributions

One of the most striking results is the stark difference between the private and public response to the COVID-19 pandemic. Table 3.3 highlights that COVID-19 led to a reduction in private contributions of over 20%, translating into a loss, on average, of $380,000 during the 2019 fiscal year. By contrast, charities exposed to the pandemic amassed an additional $975,000 in contributions from the government in fiscal year 2019, on average. As such, public contributions more than compensated for the decline in private contributions. However, despite the net increase in contributions, research by *Duquette* (2017) suggests that the withdrawal of private support may have negatively affected nonprofit savings[19].

It is also important to note that the public and private responses presented in Table 3.3 are averages, and it may be that extensive-margin responses are quite different from the intensive-margin responses. Tables T.4 and T.5 estimate separate intensive- and extensive-margin effects of COVID-19 on private contributions and government grants. Using a linear probability model, we find that organizations exposed to COVID-19 during fiscal year 2019 were just as likely to receive private support, but 5.4 percentage points more likely to receive governmental support, compared to non-exposed organizations, in fiscal year 2019 relative to fiscal year 2018. This implies that the dramatic decline in private contributions estimated in Table 3.3 is entirely an intensive margin response. Whereas, the large increase in government grants we estimate in Table 3.3 conflates an intensive-margin decline of 13.2% and an extensive-margin increase of 5.4 percentage points. Treated organizations were much more likely to receive government grants in fiscal year 2019 compared to fiscal year 2018, but the average amount of support provided by the government was smaller. However, what is clear is that the government made attempts to bolster nonprofits' finances during the pandemic. This large increase in government expenditure is at least partly due to the CARES Act, which provided emergency government support for both individuals and (nonprofit) firms. The impact of this emergency support, specifically, is discussed in Section 3.4.4.

3.4.2 Labor Market Outcomes

The next two sets of outcome variables relate to the labor market: employment and salaries. Table 3.3 shows the extent to which nonprofit workers suffered during the pandemic. On average, the number of employees declined by over 13% in fiscal year 2019 relative to fiscal year 2018. This is equivalent to the average nonprofit shedding more than 17 workers. As well as the decline in the number of employees, salaries were also cut dramatically as a result of COVID-19. Indeed,

[19] *Duquette* (2017) finds that nonprofits spend most types of revenue on program services, but are much more likely to save revenue from private contributions.

organizations exposed to COVID-19 during fiscal year 2019 reduced their total wage bill by over 40% (or over \$2 million, on average) in fiscal year 2019 relative to fiscal year 2018. Of course, the data do not permit us to know which types of employees bore the brunt of these cost savings, but work by *Lecy and Searing* (2015) suggests that nonexecutive staff wages often suffer when nonprofits face pressure to cut costs. In sum, the pandemic proved to be highly damaging for nonprofit employees, and at first glance, it appears as if the injection of government funds was not enough to prevent job loss. We return to this last point in Section 3.4.4.

3.4.3 Program Service Spending

The final outcome of interest relates to the provision of charitable services, with Table 3.3 revealing the detrimental impact that COVID-19 had on program service spending. On average, program spending fell by 34% following the onset of the pandemic. This translates to an average reduction of over \$3.9 million during the 2019 fiscal year. Therefore, although government grants more than made up for the decline in private contributions, they were not enough to prevent a reduction in program service expenses. Given local lock downs and other restrictions on service delivery, it was likely inevitable that program spending declined following the onset of the pandemic. However, these results quantify the extent of the withdrawal of charitable programs, with many of these organizations providing key social services to the local community.

3.4.4 Was PPP Effective for the Nonprofit Sector?

The previous section has illustrated how nonprofits lost workers due to the onset of the pandemic. Many of these nonprofits were eligible to receive Paycheck Protection Program loans, which were intended to help small businesses retain workers during the pandemic. This section will explore how eligibility for, and take-up of, PPP loans affected the nonprofit sector.

Table 3.4 reports estimates of Specification (3.3), which captures the effect of PPP eligibility on charities' outcomes. Eligible charities were smaller than ineligible charities. It is therefore not surprising that eligible charities lost more private contributions during the pandemic, relative to larger, ineligible charities. On the other hand, by the end of their 2019 fiscal year, PPP-eligible charities increased their employment and salaries relative to ineligible charities. This relative increase in labor force occurs despite the overall negative effect of the pandemic on employment, reported in Table 3.3. Similarly, eligible charities increased their program service spending relative to ineligible charities, even though exposure to the pandemic reduced program spending overall. Taken together, these results clearly show that PPP eligibility had a protective effect on nonprofit employment and programming.

Eligible charities also received fewer government grants during the pandemic compared to ineligible charities. For the most part, this measure of government grants does not include PPP: charities were only required to report PPP loans as government grants on the Form 990 once the loan was forgiven. While 23,388 charities had a loan approved during fiscal year 2019, only 18 charities had a PPP loan forgiven during this time.[20] These results therefore indicate that the government shifted non-PPP forms of financial support away from PPP-eligible organizations, and towards PPP-ineligible organizations, during the pandemic. Non-PPP government support for small nonprofits increased, in absolute terms: Table T.1 shows that exposure to COVID increased government grants, after controlling for the size of the organization's portfolio, and Table T.2 shows that this result persists in a subsample of filers with assets in the bottom quartile of the distribution. However, in relative terms, these results show that the government substituted between PPP and non-PPP forms of support for nonprofit organizations.

As discussed above, only 26.8% of eligible charities received a PPP loan during fiscal year 2019. Tables 3.5 and 3.6 show the relationship between take-up of these loans and charities' outcomes. The results presented in Table 3.5 show the effect of any loan take-up on each of the five outcomes, whereas the results presented in Table 3.6 estimate the relationship between the continuous amount of loan approvals and charities' outcomes. These results correspond to take-up along the extensive and intensive margins, respectively.

Simply put, early adoption of PPP loans was positively related to all five outcomes of interest. Eligible organizations which took up PPP experienced increases in employment, salaries, and program services between fiscal year 2018 and fiscal year 2019, relative to eligible organizations which did not take up PPP. Charities which took up PPP also experienced gains in their contributions, from both private and public sources, relative to charities which did not have any PPP loan approved. The estimates are qualitatively similar, regardless of whether take-up is measured

[20] These results are robust to omitting the 18 organizations which had PPP loans forgiven during fiscal year 2019.

along the intensive or extensive margin. However, the estimates produced for the extensive-margin relationships appear larger in absolute value than estimates of the corresponding relationships along the intensive margin.

Table 3.4: Impact of PPP Eligibility on Charity Outcomes

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
PPP Eligibility × After	-0.282***	-2.253***	0.121***	0.255***	0.160***
	(0.083)	(0.300)	(0.021)	(0.047)	(0.031)
PPP Eligibility	-3.346***	-4.417***	-5.350***	-7.985***	-4.844***
	(0.133)	(0.392)	(0.034)	(0.101)	(0.048)
After	0.310***	2.927***	-0.071***	-0.138***	-0.147***
	(0.086)	(0.302)	(0.014)	(0.031)	(0.032)
Constant	13.552***	9.328***	7.827***	18.149***	18.648***
	(0.159)	(0.374)	(0.015)	(0.036)	(0.043)
Observations	162733	162733	162733	162733	162733
R^2	0.017	0.030	0.197	0.063	0.122

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. Sample includes only organizations with fiscal years ending between March and November, as the Paycheck Protection Program was initiated in March 2020.

These estimates should not be interpreted as causal, as PPP take-up may simply reflect how organized, professional, and proactive a particular charity is. This will create positive bias in the estimates. If these qualities are constant over time, then the inclusion of the covariate "Any Approved Loan" will neutralize this source of bias. However, these qualities may not be constant over time, and so these estimates should be interpreted with caution.

Table 3.5: Impact of Any PPP Takeup on Charity Outcomes

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
Any Approved Loan × After	0.321***	0.641***	0.187***	0.464***	0.082***
	(0.030)	(0.067)	(0.019)	(0.052)	(0.019)
Any Approved Loan	2.559***	1.974***	1.816***	5.022***	1.156***
	(0.065)	(0.151)	(0.035)	(0.122)	(0.041)
After	-0.263***	0.327***	-0.144***	-0.404***	-0.099***
	(0.028)	(0.056)	(0.019)	(0.049)	(0.018)
Constant	9.603***	4.447***	2.050***	8.980***	13.531***
	(0.097)	(0.124)	(0.035)	(0.113)	(0.022)
Observations	155783	155783	155783	155783	155783
R^2	0.051	0.026	0.146	0.136	0.040

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. Sample includes only organizations with fiscal years ending between March and November, as the Paycheck Protection Program was initiated in March 2020. Sample includes only charities inferred eligible for Paycheck Protection Act loans, due to employing no more than 500 people at the end of fiscal year 2018.

Table 3.6: Impact of PPP Loan Approval Amount on Charity Outcomes

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
IHS(Loan Approval Amount) × After	0.039***	0.091***	0.046***	0.072***	0.039***
	(0.003)	(0.006)	(0.001)	(0.004)	(0.001)
Any Approved Loan	2.480***	1.739***	1.632***	4.815***	0.961***
	(0.066)	(0.140)	(0.034)	(0.121)	(0.039)
After	-0.310***	0.190***	-0.251***	-0.524***	-0.212***
	(0.027)	(0.056)	(0.018)	(0.048)	(0.018)
Constant	9.622***	4.502***	2.093***	9.029***	13.577***
	(0.098)	(0.124)	(0.035)	(0.113)	(0.022)
Observations	155783	155783	155783	155783	155783
R^2	0.051	0.027	0.149	0.137	0.042

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. Sample includes only organizations with fiscal years ending between March and November, as the Paycheck Protection Program was initiated in March 2020. Sample includes only charities inferred eligible for Paycheck Protection Act loans, due to employing no more than 500 people at the end of fiscal year 2018.

3.4.5 Efficacy of Government Support, by Source

The previous section has shown that PPP eligibility helped charities retain workers and keep up program service provision. It has also illustrated that governments provided relatively more grants to PPP-ineligible charities than PPP-eligible charities at the beginning of the pandemic. This section will ask whether PPP recipients' employment, salaries, and program service expenses depend on the source of their government support.

Table 3.7: Charity Outcomes as a Function of Public Support, by Source

	(1) Employees	(2) Salaries	(3) Program Services
Δ IHS(Government Grants)	0.005***	0.007***	0.007***
	(0.001)	(0.002)	(0.002)
Δ IHS(Loan Approval Amount)	0.003***	0.004***	-0.002***
	(0.000)	(0.000)	(0.000)
Observations	20872	20872	20872
R^2	0.007	0.005	0.001
F: $\beta_g = \beta_p$	1.940	2.060	23.131
$p > F$	0.170	0.157	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. Sample includes only organizations which receive PPP loan approvals during fiscal year 2019.

Table 3.7 reveals that employment and salaries increase in both forms of government support. While the magnitude of the correlation between government grants and these labor-market outcomes appears larger than the correlation between each of these outcomes and PPP loan approvals, the Wald tests are unable to reject the null hypothesis that these pairs of correlations are equal. That is, government grants appear just as effective as PPP loans at helping nonprofits retain workers and maintain their pay. The relationship between program spending and government support does vary according to the source of public funds. Charities which received additional government grants in fiscal year 2019 also tended to increase program spending, whereas charities which received PPP loan approvals tended to cut back on program spending. These results do not carry a causal interpretation. They are consistent with a story of selection, in which charities which experienced particular challenges to service delivery were also more likely to apply for PPP loans early in the pandemic.

3.5 Heterogeneity and Robustness

This section presents the results by month of filing and sector, as well as robustness to year-of-election-cycle effects.

3.5.1 Heterogeneity by Filing Month

Figure 3.3 traces out the average treatment effect of receiving a "dose" of exposure to $m-2$ months of the coronavirus pandemic, among those units which received such a dose[21], plotting the β_m^{post} coefficients from Equation 3.2.

The results in Figure 3.3 reveal a great deal of heterogeneity masked by the results presented in Table 3.3. In general, most effects are monotonic in dose level, with the magnitude of the coefficients rising (in absolute terms) as the dosage of exposure increased.

While not every coefficient is statistically distinguishable from zero, the results presented in Figure 3.3 clearly show that the average treatment effect of $m-2$ months of exposure to the pandemic on units which end the filing year in month m is increasing in m. Here we must exercise caution in interpreting these results. As *Callaway et al.* (2021) point out, a direct comparison between one of these average treatment effects and the next is the sum of two terms. The first is the average treatment of increasing the exposure to the pandemic by one additional month, thus answering the question: what would have happened to outcome Y_{imt} for nonprofits which end the filing year in month m if the pandemic had begun one month earlier? The second term is a selection term, reflecting the fact that organizations which choose to end the filing year in month m are different from organizations which choose to end the filing year in month $m+1$. We are able to trace out the path of effects of COVID-19 on organizations filing in subsequent months throughout the year, but we are not able to engage in this counterfactual exercise without imposing an additional assumption that the selection term is zero, or very close to it. Without this assumption, we may observe pairwise comparisons between local average treatment effects of a particular dose on units which received this dose, but we must not mistake it for a global average treatment effect of receiving a given dose on any unit, regardless of its characteristics. In other words: we are able to identify the treatment effect of receiving m-2 months' worth of exposure

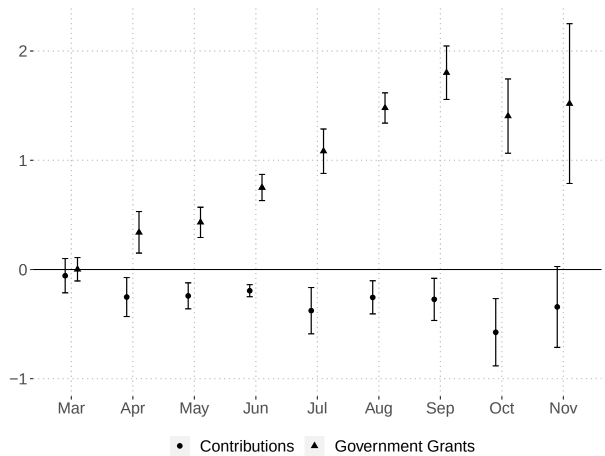
[21] These estimates are denoted $ATT(d|d)$ by *Callaway et al.* (2021)

to the pandemic on organizations which received such a dose; but we are not able to say whether organizations which select into other filing months would have been affected by the pandemic in the same way, had the timing of the pandemic been different.

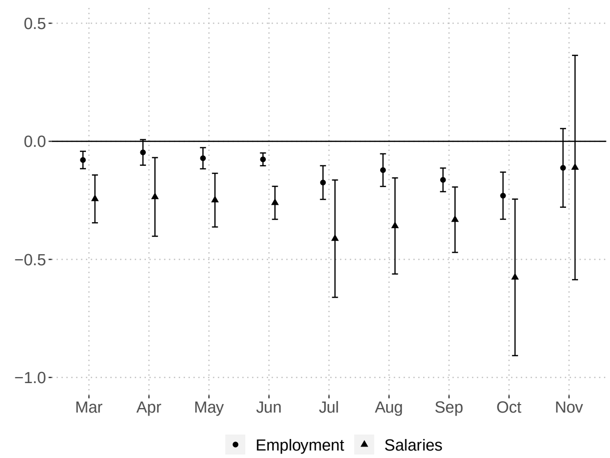
We are unwilling to rule out the existence of this selection term in part because our descriptive statistics clearly indicate the presence of selection on observables. Given that June filers are larger than charities that file in other treated months[22], one way to try and understand the direction of the bias is to restrict attention to June filers but compare the effect of COVID-19 on large versus small charities. This avoids comparing across dose groups, but mimics the type of heterogeneity that exists. In other words, this comparison is qualitatively similar to the comparison between June filers and all other charities that filed after the onset of the pandemic (as shown in Table 3.2, June filers are much larger than other filers). Doing this reveals that COVID-19 was less damaging for larger charities[23] (see Appendix Tables T.2 and T.3). This implies that the selection term on June filers might be positive, biasing these coefficients upwards. However, given that the coefficients for organizations filing later in the year are even larger (in absolute terms), the evidence still points to the fact that the longer charities were exposed to the pandemic, the more they suffered.

[22]Charities that file in the other months after the onset of COVID-19 are broadly similar to one another.

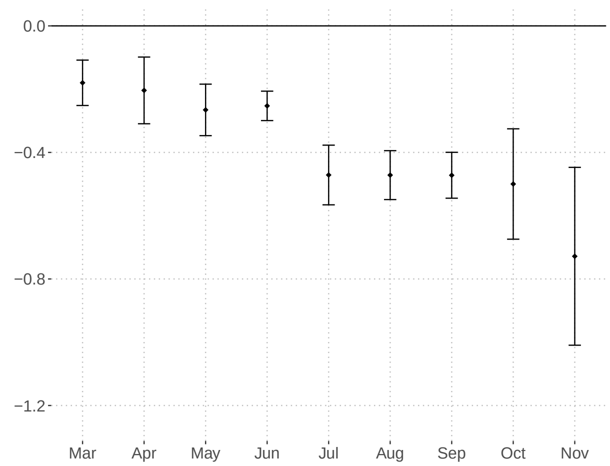
[23]Specifically, we compare June filers above the 75th percentile of total assets in FY2018 with those below the 25th percentile.



(a) Private Contributions and Government Grants



(b) Employment and Salaries



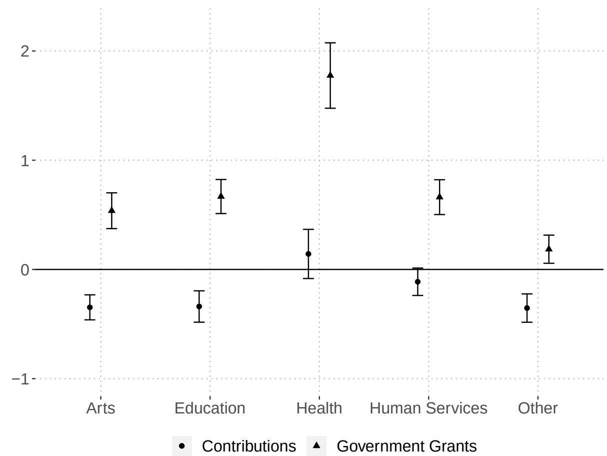
(c) Program Service Expenses

Notes: Figures depict 95% confidence intervals. Standard errors are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. All dollar figures in thousands of constant 2015 dollars.

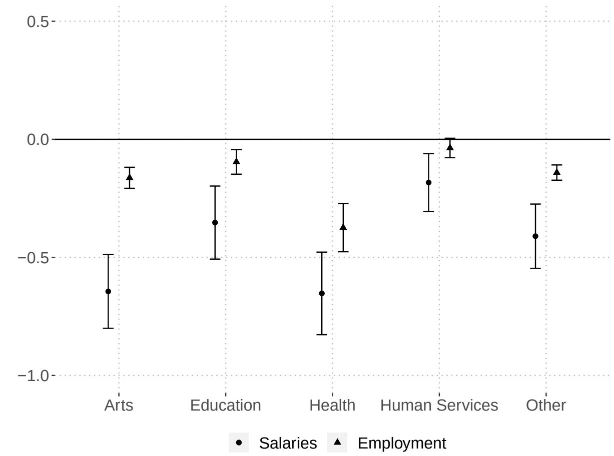
Figure 3.3: Average Treatment Effect of Dose $m - 2$

3.5.2 Heterogeneity by Sector

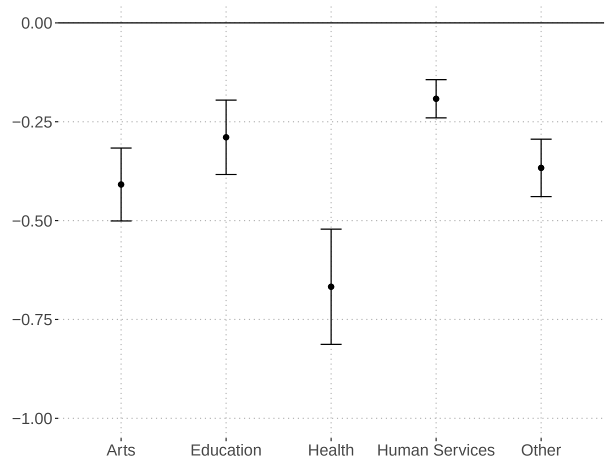
As well as heterogeneity over time, it is highly likely that the impact also varied by sector. Figure 3.4 plots the β^{post} coefficients from Equation 3.1, estimated on a sample restricted to sector k, for the five major nonprofit sectors, as defined by the NTEE. These sectors include Arts, Education, Health, Human Services, and Other.



(a) Private Contributions and Government Grants



(b) Employment and Salaries



(c) Program Service Expenses

Notes: Figures depict 95% confidence intervals. Standard errors are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. All dollar figures in thousands of constant 2015 dollars.

Figure 3.4: Average Treatment Effect by Broad Sector

Figure 3.4 confirms that the effect of the pandemic differed across broad sectors, although the overall pattern remains the same: private and public contributions respond differentially, while employment, salaries and program service expenses all decline following the onset of the pandemic. The Arts were particularly hard-hit, with contributions, program service expenses, and salaries all falling by roughly 50%[24]. The Health sector also suffered along several dimensions: on average, employment, salaries, and program spending were all negatively impacted by this crisis. Organizations in the Education and Human Services sectors proved to be slightly more robust to the pandemic,

[24] *Jensen and Bonde* (2018) provide a recent review of the literature on the physical and mental health benefits of participation in arts activities and clinical arts interventions.

suffering smaller declines in contributions and employment. However, program expenses still fell by around 20%. While we are not able to say whether the composition of the workforce remained unchanged throughout the pandemic, the fact that we find only small declines in employment in either of these sectors suggests that the pandemic may not have meaningfully reduced these organizations' capacity to provide services in the future. We cannot verify that the pandemic did not destroy match-specific human capital between employers and workers in the Human Services and Education sectors, but these results give us cause for optimism in this area, and suggests that the quality and quantity of these types of nonprofit services may be maintained in the near future.

Across all nonprofit sectors, the increase in government support between fiscal year 2018 and fiscal year 2019 for charities exposed to COVID far surpassed the corresponding change in government contributions for charities without such exposure. If funding becomes more valuable to its recipients during times of crisis, then the government should increase support to organizations with the highest marginal product. During the Great Recession, *Reich and Wimer* (2012) find that donors identify food banks as the highest marginal product organizations. During the global pandemic, we find that the government considered grants made to Health-sector organizations to have the highest marginal product. For the most part, private donors appear to have played a smaller role in helping to redirect resources.

Figure 3.4 reveals that program services were worst affected in the Health sector, followed by the Arts sector. While the negative impact on the Health sector may appear counterintuitive, it may reflect a reduction in the provision of services, such as elective procedures. Indeed, reports produced by Altarum using data from the Bureau of Labor Statistics show that the healthcare sector lost 42,500 new jobs in March 2020, the largest single month loss since reporting began in 1990. By November 2020, the level of health employment was still 3.6% below pre-COVID employment. The reduction in program spending in both Health and the Arts is consistent with local lockdowns and social distancing measures[25]. These measures posed particular challenges for Arts organizations, making it impossible for some charities in the sector to operate.

Despite Table 3.2 showing that most sectors are balanced across treatment and control groups,

[25]It is also possible that the reduction in program spending is attributable to increased precautionary savings, or a reduction in revenue. We are unable to disentangle these effects.

there still remains the concern that, if sectors are unevenly distributed across filing month, then it may be differences in dosage that are driving the sectoral effects. Appendix Figure U.1 presents average treatment effects of dose $m-2$ by sector, and shows that the patterns observed in Figure 3.4 are replicated when comparing organizations with the same filing month. In other words, even within filing month, it still appears that organizations operating in the Arts were hardest hit, while Education and Human Services fared slightly better. Thus, heterogeneity in outcomes across sectors are reflective of real differences, not differences in filing month.

3.5.3 Robustness to Year-of-Election-Cycle Effects

As discussed in Section 3.3.2, the presidential election remains the single largest potential confounder to occur during our treatment period. In order to keep from misattributing the effect of the election on charities to the pandemic, we add a third difference, comparing charities' outcomes in the run-up to the 2020 presidential election to their outcomes in the years leading to the 2016 presidential election.

The main specification is defined as follows:

$$\begin{aligned} Y_{it} = {} & \beta_1 \mathbf{1}(FilingMonth_i >= March) \cdot After_{it} \cdot \mathbf{1}(\text{2020 Election}) \\ & + \beta_2 \mathbf{1}(FilingMonth_i >= March) \cdot After_{it} + \beta_3 After_{it} \cdot \mathbf{1}(\text{2020 Election}) \\ & + \beta_4 \mathbf{1}(FilingMonth_i >= March) \cdot \mathbf{1}(\text{2020 Election}) + \beta_5 \mathbf{1}(FilingMonth_i >= March) \\ & + \beta_6 \cdot After_{it} + \beta_7 \mathbf{1}(\text{2020 Election}) + \varepsilon_{it} \end{aligned} \tag{3.7}$$

The triple-difference regression includes three sets of treatment and control groups. As before, the first treatment group is represented by the indicator variable $\mathbf{1}(FilingMonth_i >= March)$, which captures the assignment of March-November filers to a treatment group and December-February filers to a control group. But now, to reduce the possibility that the treatment effect of the pandemic on March through November filers was confounded by the 2020 election, we include another set of treatment and control groups, which nets out the effect of the presidential election cycle on charitable giving. This specification is estimated on data from fiscal years 2014, 2015, 2018, and 2019[26]. Therefore, the indicator $\mathbf{1}$(2020 Election) takes the value 1 in fiscal years 2018 and 2019, thereby capturing the two years leading up to the 2020 presidential election, and takes the value 0 for fiscal years 2014 and 2015, which are the comparable two years leading up to the 2016 presidential election. Finally, we include the indicator $After_{it}$, which takes the value 1 in fiscal years 2015 and 2019, and 0 in 2014 and 2018. The coefficient β_1 thereby captures the difference in outcome Y_{it} between March-November filers and December-February filers, in the year of the COVID-19 pandemic relative to the previous year, in the 2020 election cycle relative to the 2016 election cycle. Again, our outcomes of interest, Y_{it}, are transformed using an inverse hyperbolic sine function, and standard errors are clustered at the state level. This final difference is intended to net out the potentially confounding effect of presidential elections, one of which occurred in the middle of the COVID-19 pandemic.

Table 3.8 presents the results of the triple difference for each outcome: private contributions, government grants, employment, total wage bill and program service expenses. The coefficients on "Any Exposure · 2020 Cycle · After" correspond to the coefficients of interest, β_1.

Table 3.8 shows that controlling for the 2020 election cycle has no qualitative impact on the results: we still observe the pandemic negatively affecting charities in almost every dimension. Quantitatively, the magnitudes of the coefficients are all very similar too, with the exception of the coefficient on private contributions, which is slightly higher. This suggests that the negative impact on private contributions observed in Table 3.3 may at least be partly due to the 2020 election[27]. However, even after controlling for the election, private contributions still decline by 7.5%.

[26]Fiscal year x includes all filing year end dates between December x and November $x + 1$.
[27]*Karol* (2023a) finds that donors view charitable and political giving as substitutes.

Table 3.8: Impact of COVID-19

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
Any Exposure · 2020 Cycle · After	-0.075*	0.602***	-0.124***	-0.462***	-0.370***
	(0.041)	(0.072)	(0.025)	(0.050)	(0.030)
Any Exposure · 2020 Cycle	-0.195**	0.941***	0.051	0.399*	0.301***
	(0.088)	(0.142)	(0.086)	(0.237)	(0.091)
2020 Cycle · After	0.099***	0.006	0.097***	0.364***	0.258***
	(0.032)	(0.050)	(0.020)	(0.041)	(0.028)
Any Exposure · After	-0.127***	0.084***	-0.013	0.056	0.025
	(0.026)	(0.018)	(0.016)	(0.036)	(0.017)
Any Exposure	0.236**	1.082***	0.922***	1.800***	1.046***
	(0.092)	(0.103)	(0.106)	(0.300)	(0.090)
2020 Election Cycle	-0.368***	-8.879***	-1.067***	-2.945***	-1.021***
	(0.092)	(0.170)	(0.096)	(0.277)	(0.108)
After	0.094***	-0.073***	-0.013	-0.052	-0.039***
	(0.028)	(0.018)	(0.013)	(0.031)	(0.014)
Constant	10.677***	11.958***	2.804***	11.256***	13.688***
	(0.110)	(0.067)	(0.098)	(0.277)	(0.097)
Observations	450514	450514	450514	450514	450514
R^2	0.002	0.312	0.078	0.060	0.052

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function.

3.6 Conclusion

Survey and anecdotal evidence had suggested that the coronavirus pandemic had a particularly negative impact on the nonprofit sector. However, this paper is the first to use newly-released Form 990 data to quantify these effects. The results show that COVID-19 was damaging to charities in almost every dimension, with organizations operating in the Arts sector facing particularly difficult challenges in adapting their models of service delivery, and charities in the Health and Human Services sectors struggling to maintain employment and program services. While the increase in government funding was large, it was not enough to prevent the massive decline in program services. On average, around $4 of program service spending was lost per dollar of public funds transferred to nonprofit organizations. However, we should not conclude that this represents an inefficient use of government funds. Indeed, our results suggest that the availability of PPP loans helped to prevent further job loss. If the increased government support for charities allowed these organizations to maintain their levels of employment and salaries, then we may consider it to be money very well spent. By enabling charities to remain operational, this funding may have prevented an even larger reduction in program spending in both this period and subsequent periods. Only future work will determine whether service provision recovered, but by enabling charities to retain their workers, the PPP may have preserved match-specific human capital at nonprofits, and thereby supported the quality of services provided by these organizations during the pandemic and beyond.

APPENDICES

APPENDIX A

Implications for Optimal Deductibility of Charitable Contributions

A.1 Setup

There is a unit mass of agents, all of whom give to charity. A share $s^p \in (0, 1)$ agents also give to politicians ("political donors"), and the remainder ($s^n = 1 - s^p$) do not give to politicians ("non-political donors"). $Y = s^p y^p + s^n y^n$ represents the total amount of charitable giving made by these agents, and $P = s^p p^p$ represents the total amount of political giving made by political donors.

Recall from the charity's problem that charitable production is defined as $C(Y - F; d(\theta, \alpha(P)))$. Each type of donor receives altruistic utility from this charitable production, here denoted $C(Y, P)$ for notational simplicity. Donors also receive egoistic, or warm-glow, utility from the amount of their own gift, y.

Each donor's utility is assumed to depend on the political state, $\alpha(P)$, itself a function of P. Political donors also receive consumption utility from their own political gift, p. This consumption utility is mathematically identical to warm-glow utility.

In this economy, the government taxes labor income at constant marginal tax rate τ, and provides a demogrant of T. Charitable contributions are deductible from labor income at rate α^y. Consumption is an untaxed numeraire, and political contributions are neither taxable nor deductible from taxable income.

A.2 Agent's Problem

An agent of type $t \in \{p, n\}$ is endowed with one unit of time, which can be used for either labor (h^t) or leisure (l^t). This agent chooses work hours h^t, consumption c^t, charitable contributions y^t, and (if $t = p$) political contributions p^t to solve the following constrained maximization problem:

$$\max_{h^t, c^t, y^t, p^t} u^t(1 - h^t, c^t, y^t, p^t, C(Y, P), P) \text{ s.t. } (1 - \tau)wh^t + T = c^t + (1 - \alpha^y \tau)y^t + \mathbf{1}(t = p)p^t \quad \text{(A.1)}$$

where the fourth argument of the objective function u^t (p^t) is omitted for $t = n$.

Let $\delta_y^t \in [0, 1]$ and $\delta_p^p \in [0, 1]$ represent the extent to which a given agent understands they can affect the total amount of charitable giving Y and political giving P, respectively. The limiting case of $\delta_y^t = 0$, $\delta_p^p = 0$ represents the assumption of Sandmo (1975) that those who consume externality-producing goods do not take this externality into account at all. The limiting case of $\delta_y^t = 1$, $\delta_p^p = 1$ represents the Nash assumption employed by the bulk of the literature on voluntary public good provision, in which agents take others' contributions to the public good as given and choose a best response to that level of provision. This creates an equivalence between choosing one's own gift and choosing the aggregate amount of provision.

Let λ^t represent the marginal utility of income for an agent of type t. Assume utility is increasing and concave in each of its arguments. Finally, let wages w be drawn from a wage distribution $f(w)$. The first-order conditions of the agent's problem are:

$$- u_l^t + \lambda^t (1 - \tau) w = 0 \quad \text{(A.2)}$$

$$u_c^t + \lambda^t = 0 \quad \text{(A.3)}$$

$$u_y^t + u_{C(Y,P)}^t \frac{\partial C}{\partial Y} s^t \delta_y^t - \lambda^t (1 - \alpha^y \tau) = 0 \quad \text{(A.4)}$$

$$u_p^p + u_{C(Y,P)}^p \frac{\partial C}{\partial P} s^p \delta_p^p + u_P^p s^p \delta_p^p - \lambda^p = 0 \quad \text{(A.5)}$$

where Equation (A.5) is a first-order condition if and only if $t = p$.

Let $\rho = (\rho_l, \rho_c, \rho_y, \rho_p) = ((1-\tau)w, 1, 1-\alpha^y\tau, 1)$ be the vector of prices for leisure, consumption, charitable giving, and political giving, respectively. Let $v^t(\rho) = u^t(x(\rho))$ represent the indirect utility function for an agent of type t.

Differentiating v^t with respect to ρ_k gives:

$$\frac{\partial v^t(\rho)}{\partial \rho_k} = -u_l^t \frac{\partial h^t}{\partial \rho_k} + u_c^t \frac{\partial c^t}{\partial \rho_k} + \Big(u_y^t + u_{C(Y,P)}^t \frac{\partial C}{\partial Y} s^t \delta_y^t\Big) \frac{\partial y^t}{\partial \rho_k} + u_{C(Y,P)}^t s^{-t} \delta_y^{-t} \frac{\partial y^{-t}}{\partial \rho_k}$$
$$+ \Big(\mathbf{1}(t=p) u_p^t + u_{C(Y,P)}^t \frac{\partial C}{\partial P} s^p \delta_p^p + u_P^t s^p \delta_p^p\Big) \frac{\partial p^p}{\partial \rho_k} \tag{A.6}$$

Differentiating the budget constraint with respect to ρ_k gives:

$$\frac{\partial BC^t(\rho)}{\partial \rho_k} = (1-\tau)w \frac{\partial h^t}{\partial \rho_k} - \frac{\partial c^t}{\partial \rho_k} - (1-\alpha^y\tau)\frac{\partial y^t}{\partial \rho_k} - \mathbf{1}(t=p)\frac{\partial p^p}{\partial \rho_k} - \sum_{x \in \{h,c,y\}} \mathbf{1}(k=x)x^t - \mathbf{1}(k=p)\mathbf{1}(t=p)p^p \tag{A.7}$$

Plugging Equations (A.2) - (A.5) and (A.7) into (A.6) gives:

$$\frac{\partial v^t(\rho)}{\partial \rho_k} = -\lambda^t \Big(\sum_{x \in \{h,c,y\}} \mathbf{1}(k=x)x^t + \mathbf{1}(k=p)\mathbf{1}(t=p)p^p\Big) + u_{C(Y,P)}^t \Big(\frac{\partial C}{\partial Y}\Big(s^t \frac{\partial y^t}{\partial \rho_k}(1-\delta_y^t) + s^{-t}\frac{\partial y^{-t}}{\partial \rho_k}\Big)$$
$$+ \frac{\partial C}{\partial P} s^p \Big(\mathbf{1}(t=p)(1-\delta_p^p)\frac{\partial p^p}{\partial \rho_k} + (1-\mathbf{1}(t=p))\frac{\partial p^p}{\partial \rho_k}\Big)\Big) + u_P^t s^p \Big(\mathbf{1}(t=p)(1-\delta_p^p)\frac{\partial p^p}{\partial \rho_k}$$
$$+ (1-\mathbf{1}(t=p))\frac{\partial p^p}{\partial \rho_k}\Big) \tag{A.8}$$

A.3 Government's Problem

The government chooses tax instruments τ, $\alpha^y\tau$, T to maximize a linear social welfare function defined over the indirect utilities of each type of donor, $W^p s^p v^p(\rho) + W^n s^n v^n(\rho)$. The government must meet an exogenous revenue requirement, R_0, and must also raise sufficient revenue to pay for the demogrant T.

The government's problem can be written as follows:

$$\max_{\tau,\alpha^y\tau,T} \int W^p s^p v^p(\rho) + W^n s^n v^n(\rho) df(w) \text{ s.t. } \tau\Big(\int w \sum_t s^t h^t df(w) - \alpha^y \int \sum_t s^t y^t df(w)\Big) = R_0 + T \tag{A.9}$$

The following analysis proceeds by ruling out income effects, assuming that all donors' preferences are such that labor is additively separable from charitable and political contributions, and imposing the standard Sandmo assumption that $\delta_y^t = \delta_p^p = 0$. Further assume that preferences are such that all compensated elasticities are constant. Let β represent the marginal value of public funds; let $X = \sum_t s^t x^t$ for good x, and let $Z = wH$ represent labor income. Taking first-order conditions with respect to the marginal tax rate τ, charitable subsidy $\alpha^y\tau$, and demogrant T, and plugging in for derivatives of the indirect utility functions using (A.8):

$$Z = -\int \sum_t \frac{W^t}{\beta} s^t \lambda^t h^t df + \frac{\tau}{1-\tau} \int wh\varepsilon^h_{h,(1-\tau)w} df \tag{A.10}$$

$$Y = \int \sum_t \frac{W^t}{\beta} s^t \Big(-\lambda^t y^t + u^t_{C(Y,P)} \frac{\partial C}{\partial Y} \frac{Y}{1-\alpha^y\tau} \varepsilon^h_{y,1-\alpha^y\tau} + u^t_P \frac{P}{1-\alpha^y\tau} \varepsilon^h_{p,1-\alpha^y\tau}\Big) df - \frac{\alpha^y\tau}{1-\alpha^y\tau} \int Y\varepsilon^h_{y,1-\alpha^y\tau} df \tag{A.11}$$

$$1 = \int \sum_t \frac{W^t}{\beta} s^t \lambda^t df \tag{A.12}$$

Note that $\frac{W^t}{\beta} s^t \lambda^t y^t$ represents the marginal social value of charitable giving by donors of type t, and this term is assumed to be positive. Solve (A.11) for the optimal charitable subsidy:

$$\begin{aligned}\alpha^y\tau = &\Big[\int Y\varepsilon^h_{y,1-\alpha^y\tau} df - Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df\Big]^{-1} \Big[\int \sum_t \frac{W^t}{\beta} s^t \Big(u^t_{C(Y,P)} \frac{\partial C}{\partial Y} Y\varepsilon^h_{y,1-\alpha^y\tau} + u^t_P P\varepsilon^h_{p,1-\alpha^y\tau}\Big) df \\ &- Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df\Big]\end{aligned} \tag{A.13}$$

The denominator must be negative, as $\varepsilon^h_{y,1-\alpha^y\tau}$ represents the compensated own-price elasticity of charitable giving. The numerator will also be negative as long as aggregate political contributions do not have an implausibly large, positive impact on a given donor's utility. Mathematically, this means u_P^t has a positive upper bound, $\bar{u_P^t}$, which satisfies:

$$\int \sum_t \frac{W^t}{\beta} s^t \Big(u^t_{C(Y,P)} \frac{\partial C}{\partial Y} Y \varepsilon^h_{y,1-\alpha^y\tau} + \bar{u^t_P} P \varepsilon^h_{p,1-\alpha^y\tau} \Big) df - Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df < 0 \tag{A.14}$$

Under these circumstances, $\alpha^y\tau > 0$ and the government will optimally subsidize charity. What happens to this optimal subsidy when political contributions, P, rise?

Estimates presented in Section 1.7.2 show that $\frac{\partial Y}{\partial P} < 0$; this is consistent with results from previous work, which show that the two are substitutes. These findings imply that the denominator will clearly rise:

$$\frac{\partial}{\partial P} \Big(\int Y \varepsilon^h_{y,1-\alpha^y\tau} df - Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df \Big) = \int \frac{\partial Y}{\partial P} \varepsilon^h_{y,1-\alpha^y\tau} df - \frac{\partial Y}{\partial P} - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t \frac{\partial y^t}{\partial P} df \tag{A.15}$$

Then $\alpha^y\tau$ will increase in P if the following expression holds:

$$\alpha^y\tau > \frac{\frac{\partial}{\partial P} \Big(\int \sum_t \frac{W^t}{\beta} s^t \Big(u^t_{C(Y,P)} \frac{\partial C}{\partial Y} Y \varepsilon^h_{y,1-\alpha^y\tau} + u^t_P P \varepsilon^h_{p,1-\alpha^y\tau} \Big) df - Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df \Big)}{\frac{\partial}{\partial P} \Big(\int Y \varepsilon^h_{y,1-\alpha^y\tau} df - Y - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t y^t df \Big)} \tag{A.16}$$

Equation (A.15) shows that the denominator must be positive. To evaluate the numerator, it will be helpful to place some additional assumptions on the relationship between charitable production, utility, and political contributions. First, assume that P affects the marginal productivity of charitable spending, $\frac{\partial C}{\partial Y}$, but does not directly impact C ($\frac{\partial C}{\partial P} = 0$). Second, assume that $\frac{\partial^2 C}{\partial Y \partial P}$ cannot be "too negative" – small changes to the political environment do not drastically reduce the marginal productivity of charitable spending. Next, assume that u_P^t is constant with respect to P; however, this term is of indeterminate sign. This is because donors of different types may feel differently about the political state. For some donors, increases in P will be desirable; for others, it will not. Finally, assume $u^t_{C(Y,P),P}$ is not "too negative": the changes to the political environment do not drastically reduce the marginal utility donors receive from charitable production.

The derivative of the numerator is given by:

$$\int \sum_t \frac{W^t}{\beta} s^t \Big(u^t_{C(Y,P),P} + u^t_{C(Y,P)^2} \frac{\partial C}{\partial Y}\frac{\partial Y}{\partial P}\Big) \frac{\partial C}{\partial Y} Y \varepsilon^h_{y,1-\alpha^y\tau} + u^t_{C(Y,P)} \Big(\frac{\partial^2 C}{\partial Y^2}\frac{\partial Y}{\partial P} + \frac{\partial^2 C}{\partial Y \partial P}\Big) Y \varepsilon^h_{y,1-\alpha^y\tau}$$
$$+ u^t_{C(Y,P)} \frac{\partial C}{\partial Y}\frac{\partial Y}{\partial P} \varepsilon^h_{y,1-\alpha^y\tau} + u^t_P \varepsilon^h_{p,1-\alpha^y\tau} - \frac{\partial Y}{\partial P} - \int \sum_t \frac{W^t}{\beta} s^t \lambda^t \frac{\partial y^t}{\partial P} df \tag{A.17}$$

Most terms in (A.17) are positive. There are two exceptions: (1) $u^t_{C(Y,P)} \frac{\partial C}{\partial Y}\frac{\partial Y}{\partial P}\varepsilon^h_{y,1-\alpha^y\tau}$, which is positive, and (2) $u^t_P \varepsilon^h_{p,1-\alpha^y\tau}$, which is indeterminate, but of the same sign as u^t_P. In order for the lower bound in (A.16) to be less than 1, these two terms must remain relatively small. In particular, they must satisfy:

$$\int \sum_t \frac{W^t}{\beta} s^t \Big(u^t_{C(Y,P)} \frac{\partial C}{\partial Y}\frac{\partial Y}{\partial P} \varepsilon^h_{y,1-\alpha^y\tau} + u^t_P \varepsilon^h_{p,1-\alpha^y\tau}\Big) df < \int \frac{\partial Y}{\partial P} \varepsilon^h_{y,1-\alpha^y\tau} df$$
$$- \int \sum_t \frac{W^t}{\beta} s^t \Big(\Big(u^t_{C(Y,P),P} + u^t_{C(Y,P)^2} \frac{\partial C}{\partial Y}\frac{\partial Y}{\partial P}\Big) \frac{\partial C}{\partial Y} Y \varepsilon^h_{y,1-\alpha^y\tau} + u^t_{C(Y,P)} \Big(\frac{\partial^2 C}{\partial Y^2}\frac{\partial Y}{\partial P} + \frac{\partial^2 C}{\partial Y \partial P}\Big) Y \varepsilon^h_{y,1-\alpha^y\tau}\Big) \tag{A.18}$$

It is clear that the optimal charitable subsidy is only invariant to P in a knife's-edge case, where (A.16) holds as an equality. In any other case, the optimal charitable subsidy will change as political contributions rise. The direction of this change remains an empirical question, as further research is needed to evaluate the relative magnitudes of different terms in (A.18).

APPENDIX B

First-Stage Estimates

Table B.1: Average Effect on Charitable Fundraising and Contributions

	Log Fundraising	Log Contributions	Log Gov. Grants	Log Priv. Contrib.
# Races	0.064***	0.095***	0.139***	0.089***
	(0.003)	(0.003)	(0.007)	(0.003)
Log Personal Income/1000	864.860***	827.114***	811.202***	828.778***
	(4.145)	(3.023)	(5.587)	(3.089)
Log Population/1000	-579.222***	-614.241***	-609.349***	-610.359***
	(10.383)	(6.966)	(11.463)	(7.221)
Fundraisers' Salaries	-0.737***	-0.539***	-0.514***	-0.551***
	(0.064)	(0.041)	(0.061)	(0.043)
% Follow News	0.700***	-0.225***	-0.555***	-0.156***
	(0.056)	(0.060)	(0.115)	(0.060)
# Lagged Close Races	0.578***	0.730***	0.708***	0.721***
	(0.011)	(0.013)	(0.021)	(0.013)
% Itemizers	-79.603***	-10.841***	12.669*	-17.642***
	(3.226)	(3.778)	(7.388)	(3.718)
Observations	273,774	520,447	218,834	487,133
No. Groups	39,295	67,779	32,387	64,444

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table B.2: Average Effect on Charitable Fundraising, by Sector

	All	Arts	Education	Health	Human Services	Other
# Races	0.064***	0.090***	0.113***	0.043***	0.086***	0.036***
	(0.003)	(0.012)	(0.009)	(0.005)	(0.008)	(0.003)
Log Personal Income/1000	864.860***	829.616***	697.624***	920.300***	828.695***	865.412***
	(4.145)	(12.763)	(10.538)	(11.238)	(7.693)	(8.344)
Log Population/1000	-579.222***	-609.103***	-502.334***	-669.018***	-537.098***	-516.637***
	(10.383)	(28.178)	(20.802)	(28.601)	(17.591)	(21.421)
Fundraisers' Salaries	-0.737***	-0.770***	-0.370***	-0.600***	-0.542***	-0.540***
	(0.064)	(0.195)	(0.099)	(0.167)	(0.105)	(0.126)
% Follow News	0.700***	-0.224	0.822***	1.123***	-0.427***	1.397***
	(0.056)	(0.218)	(0.119)	(0.127)	(0.153)	(0.097)
# Lagged Close Races	0.578***	0.696***	0.331***	0.545***	0.801***	0.459***
	(0.011)	(0.045)	(0.019)	(0.025)	(0.036)	(0.013)
% Itemizers	-79.603***	-21.303	-91.674***	-124.550***	5.525	-137.881***
	(3.226)	(13.718)	(8.000)	(7.078)	(9.429)	(5.116)
Observations	273,774	32,252	48,654	38,439	91,372	63,057
No. Groups	39,295	4,479	7,037	5,677	13,187	8,915

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table B.3: Average Effect on Private Charitable Giving, by Sector

	All	Arts	Education	Health	Human Services	Other
# Races	0.089***	0.116***	0.151***	0.069***	0.126***	0.048***
	(0.003)	(0.013)	(0.011)	(0.007)	(0.009)	(0.003)
Log Personal Income/1000	828.778***	793.823***	682.036***	898.504***	805.804***	812.851***
	(3.089)	(10.065)	(7.480)	(8.113)	(6.027)	(5.832)
Log Population/1000	-610.359***	-595.179***	-517.202***	-779.701***	-592.377***	-508.119***
	(7.221)	(21.663)	(14.546)	(18.701)	(12.264)	(14.916)
Fundraisers' Salaries	-0.551***	-0.517***	-0.236***	-0.636***	-0.422***	-0.396***
	(0.043)	(0.141)	(0.068)	(0.111)	(0.070)	(0.088)
% Follow News	-0.156***	-1.100***	-0.110	0.337**	-1.549***	0.900***
	(0.060)	(0.240)	(0.138)	(0.131)	(0.157)	(0.086)
# Lagged Close Races	0.721***	0.814***	0.470***	0.730***	0.928***	0.561***
	(0.013)	(0.048)	(0.023)	(0.031)	(0.034)	(0.015)
% Itemizers	-17.642***	37.330**	-17.217*	-62.642***	82.968***	-95.700***
	(3.718)	(15.309)	(10.041)	(8.217)	(9.890)	(4.996)
Observations	487,133	48,003	85,718	80,644	164,584	108,181
No. Groups	64,444	6,133	11,271	10,802	22,082	14,155

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table B.4: Average Effect on Charitable Fundraising and Contributions, by Ideology

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
# Races	0.085***	0.062***	0.056***	0.075***	0.133***	0.084***	0.067***	0.121***
	(0.017)	(0.012)	(0.002)	(0.008)	(0.019)	(0.013)	(0.003)	(0.008)
Log Personal Income/1000	813.940***	902.170***	881.160***	846.123***	782.843***	864.562***	859.716***	795.977***
	(14.548)	(14.482)	(6.030)	(7.430)	(11.200)	(11.397)	(4.832)	(5.118)
Log Population/1000	-576.355***	-719.950***	-547.898***	-602.694***	-641.496***	-706.211***	-588.855***	-610.374***
	(33.275)	(31.851)	(15.250)	(17.213)	(24.362)	(22.911)	(12.306)	(9.978)
Fundraisers' Salaries	-1.317***	-0.615***	-0.644***	-0.611***	-0.871***	-0.409***	-0.523***	-0.372***
	(0.265)	(0.179)	(0.092)	(0.102)	(0.161)	(0.129)	(0.070)	(0.058)
% Follow News	-1.283***	0.127	1.206***	-0.400***	-2.129***	-0.639***	0.920***	-2.000***
	(0.300)	(0.221)	(0.067)	(0.145)	(0.297)	(0.227)	(0.063)	(0.144)
# Lagged Close Races	0.977***	0.785***	0.436***	0.856***	1.014***	0.911***	0.509***	1.073***
	(0.075)	(0.062)	(0.011)	(0.035)	(0.069)	(0.062)	(0.011)	(0.034)
% Itemizers	39.561**	-35.468***	-111.051***	-13.139	98.140***	20.845	-86.008***	97.674***
	(18.660)	(13.395)	(3.434)	(9.015)	(18.835)	(14.237)	(3.614)	(9.112)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table B.5: Effect of Party by Ideology: % Republican Contributions

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
# Races with Incumbents	-0.057***	-0.033***	-0.028***	-0.041***	-0.077***	-0.044***	-0.033***	-0.063***
	(0.005)	(0.003)	(0.001)	(0.002)	(0.006)	(0.003)	(0.001)	(0.002)
Dem. Incumbents - Rep. Incumbents	0.073***	0.060***	0.072***	0.069***	0.068***	0.054***	0.069***	0.066***
	(0.008)	(0.007)	(0.002)	(0.003)	(0.007)	(0.006)	(0.002)	(0.003)
Log Personal Income/1000	-526.050***	-582.675***	-527.417***	-557.010***	-520.172***	-570.081***	-523.716***	-541.220***
	(7.644)	(8.877)	(3.623)	(4.387)	(5.773)	(6.669)	(2.963)	(2.801)
Log Population/1000	750.489***	686.242***	716.193***	712.347***	712.990***	686.536***	719.677***	680.300***
	(19.103)	(19.319)	(8.720)	(10.336)	(14.181)	(14.919)	(7.314)	(6.479)
Fundraisers' Salaries	0.332***	0.096***	0.185***	0.169***	0.191***	0.061***	0.150***	0.080***
	(0.046)	(0.029)	(0.015)	(0.017)	(0.028)	(0.021)	(0.011)	(0.010)
% Follow News	0.067	-0.372***	0.010	-0.452***	0.191**	-0.158**	0.122***	-0.121***
	(0.108)	(0.095)	(0.044)	(0.052)	(0.092)	(0.081)	(0.038)	(0.040)
# Lagged Close Races	0.082***	0.012*	0.042***	0.037***	0.112***	0.015**	0.045***	0.058***
	(0.010)	(0.007)	(0.002)	(0.004)	(0.010)	(0.007)	(0.002)	(0.004)
% Itemizers	-67.369***	-43.709***	-51.788***	-43.122***	-73.493***	-54.038***	-55.309***	-59.708***
	(4.542)	(3.697)	(1.541)	(2.131)	(4.212)	(3.414)	(1.362)	(1.833)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710

Notes. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table B.6: Effect of Party by Ideology: % Democratic Contributions

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
# Races with Incumbents	0.011***	0.004*	-0.010***	0.007***	0.025***	0.013***	-0.007***	0.026***
	(0.003)	(0.002)	(0.000)	(0.001)	(0.003)	(0.003)	(0.000)	(0.002)
Dem. Incumbents - Rep. Incumbents	-0.134***	-0.106***	-0.049***	-0.137***	-0.147***	-0.121***	-0.071***	-0.166***
	(0.006)	(0.007)	(0.003)	(0.004)	(0.005)	(0.006)	(0.002)	(0.002)
Log Personal Income/1000	9.029	49.468***	-22.453***	21.864***	21.186***	51.671***	-8.396***	35.131***
	(6.326)	(7.568)	(3.067)	(3.482)	(4.830)	(5.663)	(2.499)	(2.215)
Log Population/1000	5.523	-12.221	2.503	8.731	4.272	-26.274**	-20.289***	3.015
	(13.777)	(13.941)	(6.127)	(7.191)	(10.675)	(10.803)	(5.162)	(4.577)
Fundraisers' Salaries	0.253***	0.202***	0.249***	0.205***	0.232***	0.188***	0.215***	0.174***
	(0.021)	(0.017)	(0.008)	(0.009)	(0.015)	(0.013)	(0.006)	(0.006)
% Follow News	0.221***	0.413***	0.205***	0.223***	0.159**	0.335***	0.159***	0.081***
	(0.083)	(0.081)	(0.040)	(0.043)	(0.064)	(0.065)	(0.033)	(0.029)
# Lagged Close Races	-0.152***	-0.106***	-0.035***	-0.133***	-0.209***	-0.147***	-0.056***	-0.213***
	(0.015)	(0.011)	(0.002)	(0.007)	(0.015)	(0.012)	(0.002)	(0.008)
% Itemizers	6.291*	1.745	5.387***	4.697***	11.364***	5.126**	8.048***	10.867***
	(3.321)	(3.113)	(1.554)	(1.672)	(2.663)	(2.526)	(1.282)	(1.185)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710

Notes. *$p<0.1$; **$p<0.05$; ***$p<0.01$. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

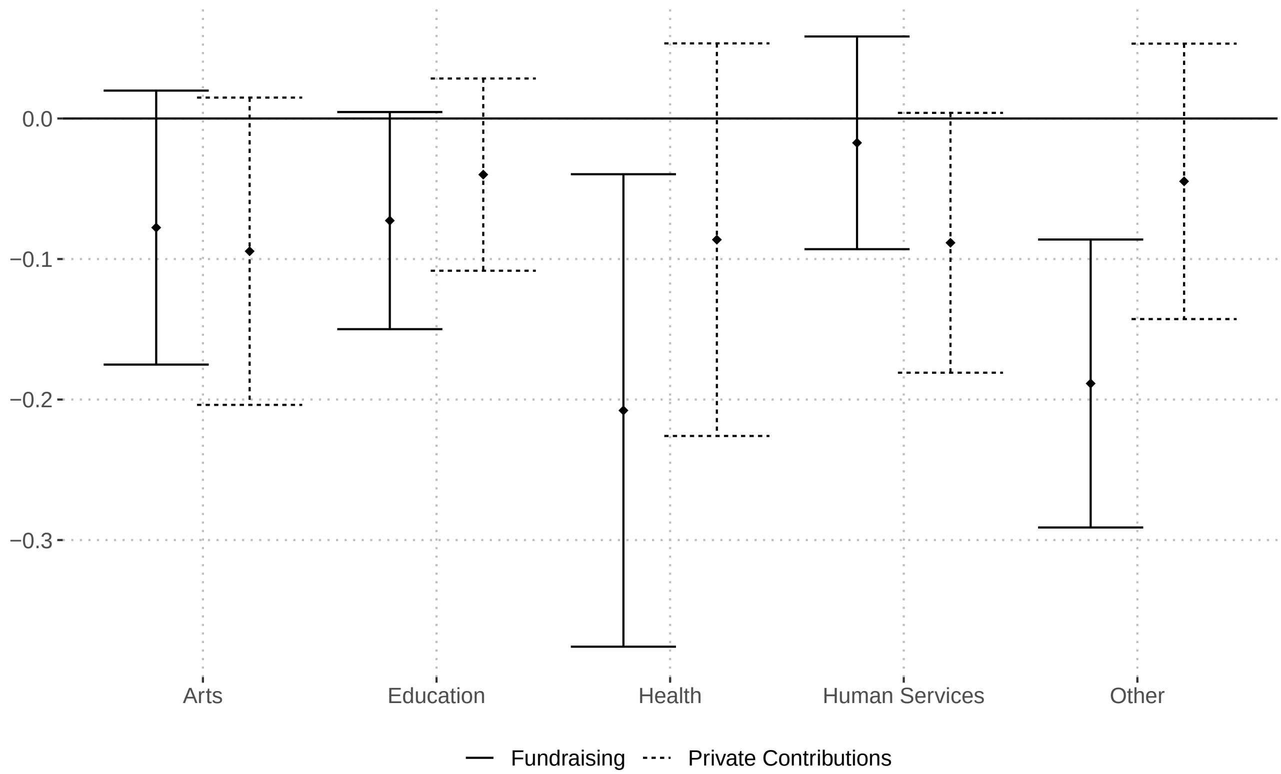
APPENDIX C

Fundraiser Subsample

Table C.1: Average Effect on Charitable Fundraising and Contributions

	Fundraising	Contributions	Gov. Grants	Priv. Contrib.
Log Political Contrib.	-0.104***	-0.069***	0.048	-0.066***
	(0.021)	(0.020)	(0.042)	(0.021)
Log Personal Income/1000	1.469***	1.737***	1.968***	1.478***
	(0.281)	(0.248)	(0.511)	(0.262)
Log Population/1000	-0.073	0.180	2.344***	0.211
	(0.470)	(0.380)	(0.760)	(0.409)
Fundraisers' Salaries	-0.000	0.001	0.003*	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	0.004***	0.007***	0.007**	0.005***
	(0.001)	(0.001)	(0.003)	(0.001)
# Lagged Close Races	0.001***	0.000***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.241***	-0.157***	0.009	-0.108*
	(0.062)	(0.057)	(0.122)	(0.063)
Observations	216,128	215,086	95,291	214,222
No. Groups	27,016	26,952	13,860	26,911
First-Stage F-Stat	628.447	630.761	246.999	629.701
Within R-squared	0.008	0.012	0.014	0.007

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.



Notes: Error bars represent 95% confidence intervals. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Figure C.1: Average Effect on Charitable Fundraising and Contributions, by Sector

Table C.2: Average Effect on Charitable Fundraising and Contributions

	Log Fundraising	Log Contributions	Log Gov. Grants	Log Priv. Contrib.
# Races	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log Personal Income/1000	8.627***	8.640***	8.424***	8.643***
	(0.044)	(0.044)	(0.077)	(0.044)
Log Population/1000	-5.845***	-5.872***	-5.317***	-5.869***
	(0.109)	(0.109)	(0.170)	(0.110)
Fundraisers' Salaries	-0.008***	-0.008***	-0.007***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	0.009***	0.009***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
# Lagged Close Races	0.005***	0.005***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.802***	-0.810***	-0.678***	-0.814***
	(0.031)	(0.031)	(0.061)	(0.031)
Observations	216,128	215,086	95,291	214,222
No. Groups	27,016	26,952	13,860	26,911

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

C.1 First-Stage Estimates

Table C.3: Average Effect on Charitable Fundraising, by Sector

	All	Arts	Education	Health	Human Services	Other
# Races	0.001***	0.001***	0.001***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Personal Income/1000	8.627***	8.240***	6.844***	9.170***	8.227***	8.751***
	(0.044)	(0.135)	(0.111)	(0.121)	(0.081)	(0.088)
Log Population/1000	-5.845***	-6.186***	-5.034***	-6.830***	-5.316***	-5.340***
	(0.109)	(0.292)	(0.212)	(0.307)	(0.186)	(0.226)
Fundraisers' Salaries	-0.008***	-0.009***	-0.003***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
% Follow News	0.009***	-0.001	0.010***	0.012***	-0.001	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
# Lagged Close Races	0.005***	0.007***	0.003***	0.005***	0.008***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.802***	-0.253*	-0.919***	-1.220***	-0.055	-1.288***
	(0.031)	(0.131)	(0.075)	(0.070)	(0.092)	(0.053)
Observations	216,128	26,712	38,224	28,824	71,496	50,872
No. Groups	27,016	3,339	4,778	3,603	8,937	6,359

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table C.4: Average Effect on Private Charitable Giving, by Sector

	All	Arts	Education	Health	Human Services	Other
# Races	0.001***	0.001***	0.001***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Personal Income/1000	8.643***	8.270***	6.842***	9.188***	8.248***	8.755***
	(0.044)	(0.135)	(0.112)	(0.122)	(0.081)	(0.089)
Log Population/1000	-5.869***	-6.237***	-5.036***	-6.895***	-5.329***	-5.369***
	(0.110)	(0.294)	(0.213)	(0.309)	(0.187)	(0.228)
Fundraisers' Salaries	-0.008***	-0.009***	-0.004***	-0.006***	-0.006***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
% Follow News	0.009***	-0.001	0.010***	0.012***	-0.001	0.014***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
# Lagged Close Races	0.005***	0.007***	0.003***	0.005***	0.007***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.814***	-0.261**	-0.933***	-1.251***	-0.070	-1.289***
	(0.031)	(0.130)	(0.075)	(0.070)	(0.092)	(0.053)
Observations	214,222	26,595	37,923	28,501	70,761	50,442
No. Groups	26,911	3,336	4,761	3,585	8,891	6,338

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

APPENDIX D

Alternative Definition of Ideology

This section describes the alternative procedure employed to measure charity ideology. It is accomplished by collecting text from charities' websites and employing supervised machine learning techniques to assign charities to one of three ideological categories. At present, only charities in the fundraiser subsample have been classified by ideology. Future work will classify a wider range of charitable organizations.

The IRS Form 990 includes the address of each charity's website, if one exists. After collecting this field from the charity's information return, each charity's website is crawled to a depth of 2. In other words, the web crawler picks up all text on the organization's homepage, as well as all links on the homepage; it then follows each link and picks up all text found on those pages. This text is then cleaned and tokenized using the R package *quanteda*. Tokens include single words, as well as a list of common phrases used to communicate culturally and politically divisive ideas on a variety of topics. These topics include abortion, immigration, firearms, the environment, foreign policy, civil rights for socially disadvantaged groups, family values, religious evangelism, and fiscal policy. Other phrases included as multi-word tokens include names of particularly divisive politicians.

At the same time, a training set of roughly 10% of organizations is hand-coded into one of three ideological categories: left, right, or center. Identification of left- and right-leaning organizations was aided by *Callahan* (2017), which discusses political activities and leanings of a number of individual charities, as well as networks of charities, on both the left and the right. Centrist organizations include community groups, such as scouting programs, after-school programs, and

Ronald McDonald House programs. After categorizing these organizations, a random sample of the remaining organizations were selected in order to build a training set large enough to be useful for categorization. When any organization is not clearly oriented towards the political left or right, it is assigned to the center category.

Finally, the tokenized corpus of text is formed into a document feature matrix, and weighted by inverse document frequency. A Bernoulli naÃ¯ve Bayes classifier is trained on the hand-coded subset of documents in this matrix. The resulting confusion matrix is presented in Table D.1. The model priors are determined by the distribution of charities across ideologies in the training set, where approximately half of all organizations are classified as centrist, and the remaining half is roughly evenly split across the political left and right. Per the confusion matrix, the model's accuracy is estimated at 81.21%[1].

Table D.1: Confusion Matrix

		Predicted Class		
		Center	Left	Right
	Center	945	106	7
Actual Class	Left	66	352	11
	Right	81	71	181

The distribution of ideology across charities is presented in Figure D.1. In the Other category, more than half of the organizations are identified as having either a left or a right-leaning ideology. This category includes many organizations with politically-oriented missions, including environmental groups, think tanks, and non-congregational religious groups. Left-leaning ideology is also prevalent in the arts category, and a sizable minority of Education and Human Services organizations are left-leaning. After the Other category, the next-largest concentration of right-leaning organizations is found in education and human services. A lot of the education groups will be oriented towards school choice or parents' rights movements. The health sector is the least ideological sector, though it does have a notable presence of ideological groups, many of which will be related to abortion or family planning.

[1]95% confidence interval: (79.34%, 82.98%)

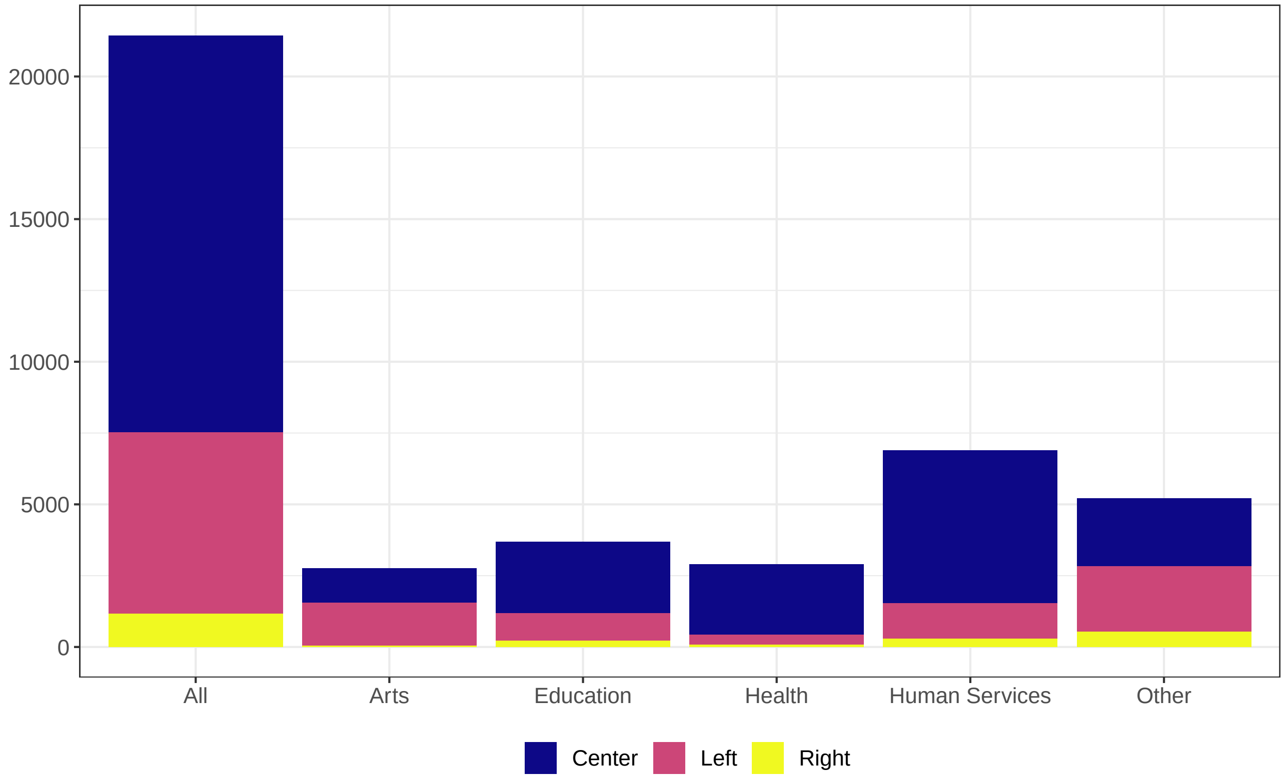


Figure D.1: Categorical Ideology by Charity Sector (Naive Bayes Classification)

Tables D.2 and D.3 are analogous to Tables 1.4 and J.1, using this definition of the ideology measure instead of the one produced using the Gentzkow-Shapiro algorithm. The results are qualitatively consistent with those presented in Section 1.5.

Table D.2: Elasticities of Charitable Fundraising and Contributions by Ideology (Naive Bayes Classification)

	Log Fundraising			Log Private Contributions		
	Left	Right	Center	Left	Right	Center
Log Political Contrib.	-0.116***	-0.348	-0.098***	-0.092*	-0.232	-0.067**
	(0.043)	(0.269)	(0.035)	(0.048)	(0.225)	(0.034)
Log Personal Income/1000	2.110***	4.246	1.273***	1.386**	2.384	1.579***
	(0.575)	(2.773)	(0.430)	(0.586)	(2.289)	(0.394)
Log Population/1000	-0.392	-1.694	-0.162	-0.309	-1.682	-0.183
	(0.915)	(2.530)	(0.666)	(0.845)	(2.105)	(0.570)
Fundraisers' Salaries	-0.006***	0.003	-0.001	-0.004*	0.000	0.000
	(0.002)	(0.004)	(0.001)	(0.002)	(0.003)	(0.001)
% Follow News	0.006**	0.005	0.005***	-0.003	0.016**	0.009***
	(0.003)	(0.008)	(0.002)	(0.003)	(0.006)	(0.002)
# Lagged Close Races	0.001***	0.002	0.001***	0.001***	0.001	0.001*
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
% Itemizers	-0.272**	-0.448	-0.147*	0.234*	-0.305	-0.193**
	(0.131)	(0.396)	(0.086)	(0.136)	(0.346)	(0.087)
Observations	51,064	9,271	111,160	50,822	9,237	110,356
No. Groups	6,383	1,159	13,895	6,380	1,157	13,847
First-Stage F-Stat	195.968	16.473	274.287	196.978	16.957	275.080
Within R-squared	0.020	-0.024	0.012	0.014	-0.010	0.010

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table D.3: Elasticities of Charitable Fundraising and Contributions by Ideology and Party (Naive Bayes Classification)

	Left	Right	Center	Left	Right	Center
Share Rep. Contrib.	0.032***	-0.280	0.014***	0.026**	-0.174	0.010***
	(0.011)	(0.215)	(0.004)	(0.011)	(0.148)	(0.004)
Share Dem. Contrib.	-0.035***	0.238	-0.019***	-0.030**	0.151	-0.016***
	(0.013)	(0.188)	(0.005)	(0.012)	(0.129)	(0.005)
Log Personal Income/1000	7.257***	-51.738	3.679***	5.696***	-32.586	3.501***
	(2.208)	(41.081)	(0.988)	(2.174)	(28.170)	(0.892)
Log Population/1000	-6.740***	67.731	-3.822***	-5.633**	41.735	-3.100***
	(2.561)	(53.826)	(1.352)	(2.530)	(36.808)	(1.199)
Fundraisers' Salaries	-0.003	-0.015	0.001	-0.001	-0.011	0.002*
	(0.002)	(0.017)	(0.001)	(0.002)	(0.012)	(0.001)
% Follow News	0.012***	0.056	0.006***	0.002	0.048	0.009***
	(0.004)	(0.052)	(0.002)	(0.004)	(0.035)	(0.002)
# Lagged Close Races	-0.001**	0.001	0.000	-0.000	0.001	-0.000
	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
% Itemizers	0.398*	-4.772	0.205*	0.789***	-2.939	0.067
	(0.230)	(3.724)	(0.113)	(0.235)	(2.534)	(0.111)
Observations	51,064	9,271	111,160	50,822	9,237	110,356
No. Groups	6,383	1,159	13,895	6,380	1,157	13,847
S-W F-Stat: Rep. Contrib	146.401	2.206	613.735	146.887	2.019	613.137
S-W F-Stat: Dem. Contrib	156.844	2.242	757.142	157.447	2.050	752.947
Within R-squared	-0.138	-10.615	-0.019	-0.096	-6.672	-0.016

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

APPENDIX E

Back-of-the-Envelope Calculations

The objective of this calculation is to determine the amount of private charitable giving that would be lost if donors had made another \$1 billion in political contributions during the 2016 election cycle. As the specifications are estimated using a log-log transformation, each charity's counterfactual levels of contributions can be recovered using the following expression:

$$\Delta \ln(Y_i) = \hat{\beta} \Delta \ln(P_{m(i)}) \tag{E.1}$$

where Y_i represents private contributions to charity i, and $\hat{\beta}$ is therefore the estimate produced in column 4 of Table 1.3. The first step to evaluating this expression is to calculate values for $\Delta \ln(P_{m(i)})$, the counterfactual level of political contributions in each charity's market. The share of the additional \$1 billion attributed to donors in each state s is assumed equal to that state's share of total political contributions in the 2016 cycle, ϕ_s. Each charity's market-level exposure to the additional political contributions, in billions, is therefore calculated as:

$$\psi_i = \sum_{s \in m(i)} \phi_s \tag{E.2}$$

This implies the following relationship between $P_{m(i)t}$ and P_t, the total amount of political contributions made in the United States in year t:

$$P_{m(i)t} = \psi_i P_t \tag{E.3}$$

The counterfactual level of $P_{m(i)t}$, denoted $P'_{m(i)t}$, can be expressed as follows:

$$P'_{m(i)t} - P_{m(i)t} = \psi_i (P'_t - P_t) \tag{E.4}$$

where $P'_t - P_t = \Delta P_t$ takes the value of \$1 billion. The next step is to derive a formula for $\Delta \ln(P_{m(i)})$:

$$\frac{P'_{m(i)t}}{P_{m(i)t}} - 1 = \frac{\Delta P_t}{P_{m(i)t}} \psi_i \tag{E.5}$$

$$\frac{P'_{m(i)t}}{P_{m(i)t}} = 1 + \frac{\Delta P_t}{P_{m(i)t}} \psi_i \tag{E.6}$$

$$\Delta \ln(P_{m(i)t}) = \ln(1 + \frac{\Delta P_t}{P_{m(i)t}} \psi_i) \tag{E.7}$$

This expression can be plugged into (E.1) to recover $\Delta \ln(Y_i)$, the difference in private charitable contributions received by charity i if large political donors had collectively given an additional \$1 billion to political campaigns in 2016. The implied magnitude of the change in aggregate private charity is calculated as $\sum_i (Y'_i - Y_i)$, where $\sum_i Y'_i$ is derived as follows:

$$\Delta \ln(Y_i) = \hat{\beta} \Delta \ln(P_{m(i)}) \tag{E.8}$$

$$\ln(Y'_i) = \ln(Y_i) + \hat{\beta} \Delta \ln(P_{m(i)}) \tag{E.9}$$

$$Y'_i = \exp(\ln(Y_i) + \hat{\beta} \Delta \ln(P_{m(i)})) \tag{E.10}$$

$$\sum_i Y'_i = \sum_i (\exp(\ln(Y_i) + \hat{\beta} \Delta \ln(P_{m(i)}))) \tag{E.11}$$

and $\sum_i Y_i$ is simply the observed sum of charitable contributions to these organizations in 2016.

E.1 Back-of-the-Envelope Calculation, Holding Fundraising Constant

Fundraising-constant estimates of the effect of political contributions on private charity are presented in Table 1.5. These estimates are presented as $\frac{\partial Y_{it(i)}}{\partial P_{m(i)t(i)}}$, and they are estimated on a subsample of organizations which report strictly positive levels of fundraising for each fiscal year in the sample. Per Table 1.5, the 95% confidence interval for $\frac{\partial \hat{Y_{it(i)}}}{\partial P_{m(i)t(i)}}$ is given by $(-0.532, 1.182)$. As $Y_{it(i)}$ is measured in thousands of constant 2015 dollars, and $P_{m(i)t(i)}$ is measured in millions of constant 2015 dollars, one can interpret these estimates to mean that for each million dollars of political contributions originating from among the charity's potential donors, the charity may lose as much as \$532 in private contributions, or may gain as much as \$1,182 in private contributions.

How much crowd-out do these figures imply? Let $\hat{\beta} := \frac{\partial \hat{Y_{it(i)}}}{\partial P_{m(i)t(i)}}$. Note that:

$$Y_{it(i)} = \hat{\beta} P_{m(i)t(i)} \Rightarrow \Delta Y_{it(i)} = b\hat{eta} \Delta P_{m(i)t(i)} \tag{E.12}$$

As above, $\Delta P_{m(i)t(i)}$ takes the value of \$1 billion; for this linear specification, $P_{m(i)t(i)}$ are measured in millions, and so it is useful to express $\Delta Y_{it(i)}$ as follows:

$$\Delta Y_{it(i)} = \hat{\beta} 1000 \psi_i \tag{E.13}$$

The object of interest remains the change in aggregate private charity is calculated as $\sum_i (Y'_{it(i)} - Y_{it(i)})$, or alternatively, $\sum_i \Delta Y_{it(i)}$. This can be calculated as:

$$\sum_i \Delta Y_{it(i)} = \hat{\beta} 1000 \sum_i \psi_i \tag{E.14}$$

Plugging the bounds of the 95% confidence interval in for $\hat{\beta}$, and restricting i to refer only to this "always-fundraiser" set of charities, implies that political contributions may crowd out charitable contributions by as much as \$1.73 per dollar, or may crowd in charitable contributions by as much as \$3.85 per dollar. However, these figures are not strictly comparable to the \$2.9/dollar degree of crowd-out measured when charities adjust their fundraising expenses; the sample used to obtain these estimates includes all charities. To obtain a comparable estimate of fundraising-constant crowd-out, it will be necessary to sum the fundraising-constant crowd-out experienced at always-fundraising charities with that experienced at sometimes-fundraising and never-fundraising charities. Per Table E.1, charities which never report positive fundraising expenses do not appear sensitive to political contributions. Therefore the comparable estimate of fundraising-constant crowd-out will reflect effects felt by always- and sometimes-fundraisers. Per Table K.1, these organizations together may lose \$490 per million dollars of political contributions, on average. The 95% confidence interval for $\hat{\beta}$ in Table K.1 is given by (-0.321, 1.301). By plugging these bounds in for $\hat{\beta}$, and summing over always- and sometimes-fundraiser charities, we see that political contributions may crowd out charitable contributions by as much as \$1.50, or may crowd in charitable contributions by as much as \$6.067. Notably, the headline crowd-out figure of \$2.9 per dollar does not fall within the 95% confidence interval of implied crowd-out, after controlling for fundraising expenses.

Table E.1: Elasticities of Private Charitable Contributions to Political Contributions, by Fundraiser Group

	Always-Fundraisers	Sometimes-Fundraisers	Never-Fundraisers
Log Political Contrib.	-0.066***	-0.102*	-0.031
	(0.021)	(0.056)	(0.031)
Log Personal Income/1000	1.478***	1.950***	1.149**
	(0.262)	(0.596)	(0.466)
Log Population/1000	0.211	1.605*	-0.539
	(0.409)	(0.915)	(0.877)
Fundraisers' Salaries	-0.000	0.002	-0.000
	(0.001)	(0.002)	(0.002)
% Follow News	0.005***	-0.006*	-0.004
	(0.001)	(0.003)	(0.004)
# Lagged Close Races	0.001***	0.002*	0.001
	(0.000)	(0.001)	(0.001)
% Itemizers	-0.108*	0.221	0.005
	(0.063)	(0.154)	(0.186)
Observations	214,222	117,492	155,419
No. Groups	26,911	15,268	22,265
First-Stage F-Stat	629.701	97.670	416.061
Within R-squared	0.007	0.000	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table E.2: First-Stage: Elasticities of Private Charitable Contributions to Political Contributions, by Fundraiser Group

	Always-Fundraisers	Sometimes-Fundraisers	Never-Fundraisers
# Races	0.060***	0.120***	0.256***
	(0.002)	(0.012)	(0.013)
Log Personal Income/1000	864.286***	784.262***	744.895***
	(4.405)	(6.929)	(6.149)
Log Population/1000	-586.921***	-596.806***	-652.099***
	(10.965)	(13.757)	(11.653)
Fundraisers' Salaries	-0.815***	-0.257***	-0.000
	(0.075)	(0.070)	(0.048)
% Follow News	0.870***	-2.293***	-5.136***
	(0.055)	(0.201)	(0.174)
# Lagged Close Races	0.529***	1.130***	1.248***
	(0.011)	(0.049)	(0.048)
% Itemizers	-81.404***	108.604***	297.045***
	(3.123)	(12.694)	(10.926)
Observations	214,222	117,492	155,419
No. Groups	26,911	15,268	22,265

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

APPENDIX F

Supporting Tables, Components of Fundraising Response

Table F.5: Estimated Components of Fundraising Response, Controlling for Liabilities to Assets Ratio

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	39.942***	23.543***	27.35***	23.365***	43.729***	56.637***
	(2.467)	(4.869)	(5.249)	(4.013)	(4.933)	(5.64)
$\frac{\partial Y}{\partial P}$	0.325	-0.317	-0.650	0.980	-1.130	1.916*
	(0.437)	(0.796)	(1.583)	(1.205)	(0.770)	(1.013)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.230***	-0.113	-0.078	-0.288**	0.013	-0.571***
	(0.050)	(0.072)	(0.058)	(0.122)	(0.121)	(0.161)
Observations	203,304	25,637	35,918	26,886	67,782	47,081
No. Groups	26,339	3,285	4,644	3,500	8,751	6,159

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). The underlying equations used to produce these estimates include a control for the ratio of total liabilities to assets on the charity's balance sheet at the beginning of its fiscal year. Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

Table F.1: Estimates of Equation (1.7)

	All	Arts	Education	Health	Human Services	Other
Log Political Contrib.	-0.048**	-0.047	-0.001	-0.102	-0.120**	0.020
	(0.023)	(0.058)	(0.061)	(0.068)	(0.048)	(0.047)
Log Fundraising	0.799***	0.923***	0.620***	0.627***	0.893***	0.820***
	(0.056)	(0.197)	(0.140)	(0.136)	(0.113)	(0.093)
Log Fund. × Log Pol. Contrib.	0.010**	0.003	-0.003	0.026**	0.006	0.013*
	(0.004)	(0.016)	(0.012)	(0.012)	(0.010)	(0.007)
Log Personal Income/1000	0.376	0.246	0.699	0.289	1.434**	-0.684
	(0.290)	(0.737)	(0.576)	(0.965)	(0.571)	(0.633)
Log Population/1000	0.246	-1.791	-0.218	2.303	-0.379	0.882
	(0.475)	(1.202)	(1.070)	(1.442)	(0.920)	(0.942)
Fundraisers' Salaries	-0.000	-0.001	0.001	0.002	-0.001	-0.003
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
% Follow News	0.003*	-0.006	0.003	0.011**	0.004	-0.001
	(0.002)	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)
# Lagged Close Races	-0.000	0.001	0.000	-0.000	0.001*	-0.001*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
% Itemizers	0.039	0.317	0.135	-0.312	-0.000	0.171
	(0.078)	(0.226)	(0.236)	(0.230)	(0.135)	(0.168)
Observations	203,112	25,626	35,879	26,858	67,723	47,026
No. Groups	26,136	3,273	4,604	3,472	8,690	6,097
S-W F-Stat: # Races	1,007.394	167.680	128.312	131.717	189.378	334.186
S-W F-Stat: Log Fundraising	1,519.123	111.048	190.912	255.100	272.492	699.669
S-W F-Stat: Log Fund. × # Races	1,396.048	124.286	160.959	219.569	209.394	699.839

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table F.2: First-Stage Estimates of Equation (1.7) (Dependent Variable: # Races)

	All	Arts	Education	Health	Human Services	Other
# Races	0.134***	0.232***	0.168***	0.088***	0.152***	0.098***
	(0.006)	(0.028)	(0.021)	(0.009)	(0.016)	(0.007)
Log Liabilities	1.445***	2.295***	1.402***	1.128***	0.956***	1.565***
	(0.105)	(0.356)	(0.338)	(0.249)	(0.234)	(0.172)
# Races × Log Liabilities	-0.011***	-0.022***	-0.010***	-0.007***	-0.012***	-0.009***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)
Log Personal Income/1000	858.168***	812.401***	664.426***	922.383***	818.928***	881.985***
	(4.673)	(14.406)	(11.850)	(12.914)	(8.504)	(9.350)
Log Population/1000	-573.793***	-608.689***	-481.687***	-683.263***	-512.018***	-538.273***
	(11.394)	(30.042)	(21.742)	(32.222)	(19.470)	(23.973)
Fundraisers' Salaries	-0.771***	-0.742***	-0.213**	-0.565***	-0.626***	-0.628***
	(0.076)	(0.216)	(0.107)	(0.200)	(0.128)	(0.154)
% Follow News	0.585***	-0.777***	0.713***	1.060***	-0.229	1.116***
	(0.066)	(0.280)	(0.151)	(0.145)	(0.165)	(0.116)
# Lagged Close Races	0.506***	0.612***	0.283***	0.472***	0.718***	0.403***
	(0.011)	(0.042)	(0.018)	(0.023)	(0.036)	(0.013)
% Itemizers	-65.819***	18.992	-80.707***	-117.235***	0.534	-110.189***
	(3.825)	(17.909)	(10.400)	(7.958)	(10.000)	(6.265)
Observations	203,112	25,626	35,879	26,858	67,723	47,026
No. Groups	26,136	3,273	4,604	3,472	8,690	6,097

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table F.3: First-Stage Estimates of Equation (1.7) (Dependent Variable: Log Fundraising)

	All	Arts	Education	Health	Human Services	Other
# Races	-0.007***	-0.009	-0.008	-0.010*	0.008	-0.012***
	(0.003)	(0.008)	(0.009)	(0.006)	(0.005)	(0.004)
Log Liabilities	5.539***	4.268***	5.761***	5.651***	5.651***	5.933***
	(0.303)	(0.798)	(0.817)	(0.840)	(0.566)	(0.553)
# Races × Log Liabilities	0.000	0.000	0.000	0.000	-0.001	0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Log Personal Income/1000	55.495***	44.372	59.520	100.864**	37.175	81.222**
	(17.925)	(44.820)	(47.174)	(49.546)	(31.828)	(39.716)
Log Population/1000	51.762	110.450	45.003	-169.246	130.276	-15.707
	(44.455)	(110.857)	(110.973)	(125.912)	(79.629)	(90.926)
Fundraisers' Salaries	0.042	0.212	-0.281	-0.172	0.155	0.116
	(0.082)	(0.233)	(0.177)	(0.219)	(0.143)	(0.182)
% Follow News	0.228*	0.296	0.149	-0.202	0.220	0.607**
	(0.137)	(0.387)	(0.366)	(0.395)	(0.235)	(0.286)
# Lagged Close Races	0.028***	0.035	0.034*	0.062***	-0.014	0.032***
	(0.008)	(0.025)	(0.017)	(0.021)	(0.018)	(0.012)
% Itemizers	-15.197**	-31.807*	-9.084	6.714	-10.755	-28.031**
	(5.977)	(17.186)	(19.059)	(17.749)	(10.196)	(12.264)
Observations	203,112	25,626	35,879	26,858	67,723	47,026
No. Groups	26,136	3,273	4,604	3,472	8,690	6,097

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table F.4: First-Stage Estimates of Equation (1.7) (Dependent Variable: Log Fundraising × # Races)

	All	Arts	Education	Health	Human Services	Other
# Races	0.179***	0.420***	0.268***	0.005	0.230***	0.078*
	(0.028)	(0.117)	(0.094)	(0.059)	(0.067)	(0.040)
Log Liabilities	27.267***	21.542***	28.270***	27.839***	24.148***	30.402***
	(1.631)	(4.213)	(4.457)	(4.596)	(3.056)	(3.005)
# Races × Log Liabilities	0.023***	-0.000	0.030**	0.029***	0.032***	0.025***
	(0.003)	(0.012)	(0.012)	(0.006)	(0.010)	(0.005)
Log Personal Income/1000	4272.525***	3892.626***	3910.090***	4912.272***	3770.148***	4503.475***
	(101.501)	(251.288)	(270.579)	(277.692)	(178.401)	(226.696)
Log Population/1000	-2213.288***	-1804.692***	-2111.065***	-3785.973***	-1539.014***	-2398.249***
	(245.838)	(602.043)	(615.983)	(690.946)	(437.701)	(507.120)
Fundraisers' Salaries	-0.622	0.863	-0.371	-0.162	0.174	0.666
	(0.524)	(1.480)	(1.082)	(1.447)	(0.871)	(1.111)
% Follow News	1.489*	-3.673	1.911	3.788*	-0.380	6.564***
	(0.792)	(2.317)	(2.134)	(2.197)	(1.414)	(1.656)
# Lagged Close Races	2.609***	3.140***	1.909***	2.783***	3.019***	2.096***
	(0.077)	(0.270)	(0.168)	(0.193)	(0.200)	(0.111)
% Itemizers	-244.361***	-12.029	-295.789***	-438.301***	-9.191	-495.156***
	(35.021)	(110.091)	(111.771)	(98.547)	(65.263)	(71.574)
Observations	203,112	25,626	35,879	26,858	67,723	47,026
No. Groups	26,136	3,273	4,604	3,472	8,690	6,097

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

APPENDIX G

Supporting Tables, Advertising Specifications

Table G.1: Estimates of Equation (1.1), FY 2012-2018

	All	Arts	Education	Health	Human Services	Other
Log Political Contrib.	-0.083***	-0.172***	-0.015	-0.064	-0.114**	-0.077*
	(0.021)	(0.059)	(0.044)	(0.059)	(0.046)	(0.044)
Log Personal Income/1000	1.629***	2.113***	1.370**	1.425*	1.964***	1.502***
	(0.282)	(0.746)	(0.613)	(0.800)	(0.557)	(0.570)
Log Population/1000	0.128	-1.745	0.184	0.698	0.915	-0.913
	(0.565)	(1.480)	(1.367)	(1.649)	(1.094)	(1.055)
Fundraisers' Salaries	-0.005*	-0.015*	0.006	0.003	-0.008	-0.009
	(0.003)	(0.008)	(0.006)	(0.008)	(0.005)	(0.006)
% Follow News	0.009***	0.007	0.008	0.010*	0.008**	0.009**
	(0.002)	(0.006)	(0.005)	(0.006)	(0.004)	(0.004)
# Lagged Close Races	0.000***	0.001***	-0.000	0.000	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-0.573	2.561	-5.023***	-0.132	0.277	-0.322
	(0.629)	(1.727)	(1.673)	(1.756)	(1.203)	(1.271)
Observations	160,636	19,950	28,442	21,374	53,043	37,827
No. Groups	26,886	3,334	4,755	3,582	8,881	6,334
First-Stage F-Stat	2,144.182	161.740	229.505	477.473	290.614	930.303
Within R-squared	0.008	0.007	0.010	0.007	0.009	0.009

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Additional tables available upon request.

Table G.2: First-Stage Estimates of Equation (1.1), FY 2012-2018

	All	Arts	Education	Health	Human Services	Other
# Races	0.095***	0.117***	0.129***	0.083***	0.134***	0.061***
	(0.002)	(0.009)	(0.008)	(0.004)	(0.006)	(0.002)
Log Personal Income/1000	919.452***	900.635***	700.249***	962.527***	917.278***	883.275***
	(2.807)	(9.039)	(8.311)	(7.008)	(5.259)	(6.186)
Log Population/1000	-1279.011***	-1148.378***	-1063.271***	-1436.921***	-1262.827***	-1248.438***
	(6.675)	(19.357)	(14.137)	(17.507)	(12.954)	(13.140)
Fundraisers' Salaries	-8.020***	-8.140***	-5.997***	-8.607***	-6.750***	-8.185***
	(0.069)	(0.251)	(0.157)	(0.170)	(0.152)	(0.129)
% Follow News	4.864***	4.361***	3.406***	5.375***	3.721***	5.523***
	(0.059)	(0.248)	(0.152)	(0.126)	(0.159)	(0.088)
# Lagged Close Races	0.251***	0.273***	0.231***	0.227***	0.291***	0.206***
	(0.004)	(0.016)	(0.011)	(0.010)	(0.011)	(0.006)
% Itemizers	1722.852***	1633.226***	1440.313***	1856.872***	1590.283***	1813.221***
	(10.357)	(36.924)	(27.006)	(25.584)	(22.895)	(18.851)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table G.3: Estimates of Equation (1.14)

	All	Arts	Education	Health	Human Services	Other
Log Political Contrib.	-0.020	0.022	0.015	-0.035	-0.041*	-0.033
	(0.012)	(0.033)	(0.032)	(0.035)	(0.022)	(0.025)
Log Number of Ads	-0.081***	-0.109**	-0.099	-0.112**	-0.034	-0.112**
	(0.019)	(0.048)	(0.071)	(0.057)	(0.025)	(0.044)
Log Personal Income/1000	2.452***	1.325	1.861	3.282***	2.044***	3.390***
	(0.377)	(0.938)	(1.197)	(1.210)	(0.527)	(0.783)
Log Population/1000	1.810***	0.812	5.668***	1.911	0.975	0.299
	(0.589)	(1.545)	(1.817)	(1.652)	(0.994)	(1.114)
Fundraisers' Salaries	0.002	0.009	0.006	0.002	-0.005	0.007
	(0.003)	(0.007)	(0.006)	(0.007)	(0.004)	(0.005)
% Follow News	0.005**	0.006	0.004	0.003	0.002	0.013***
	(0.002)	(0.005)	(0.007)	(0.005)	(0.003)	(0.004)
# Lagged Close Races	-0.000	-0.001*	-0.001*	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	-6.414***	-6.246	-9.214*	-7.926*	-2.228	-8.821***
	(1.567)	(3.858)	(5.166)	(4.704)	(2.159)	(3.304)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995
SW F-Stat: Log Pol. Contrib.	72,244.124	17,500.935	17,895.151	2,585.121	59,527.670	5,377.869
SW F-Stat: Log Ads	1,242.200	167.539	227.695	156.273	523.898	234.405
Within R-squared	-0.000	-0.002	0.000	-0.001	0.001	-0.001

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table G.4: First-Stage Estimates of Equation (1.14) (Dependent Variable: Log Pol. Contrib)

	All	Arts	Education	Health	Human Services	Other
# Races	0.067***	0.080***	0.080***	0.062***	0.087***	0.054***
	(0.001)	(0.005)	(0.005)	(0.002)	(0.004)	(0.001)
Avg. Cost per Minute	403256.038***	382702.674***	411300.574***	391882.018***	387659.862***	405183.155***
	(1354.420)	(5417.166)	(4555.509)	(2945.087)	(3827.561)	(2309.287)
Log Personal Income/1000	410.391***	421.410***	336.065***	454.347***	411.513***	407.471***
	(3.145)	(10.244)	(7.239)	(7.783)	(5.857)	(6.738)
Log Population/1000	-539.144***	-541.298***	-443.589***	-704.367***	-538.778***	-498.597***
	(6.681)	(20.059)	(13.728)	(17.405)	(11.923)	(13.427)
Fundraisers' Salaries	-4.278***	-4.484***	-2.963***	-4.810***	-3.491***	-4.403***
	(0.047)	(0.160)	(0.093)	(0.124)	(0.088)	(0.099)
% Follow News	6.022***	5.398***	5.259***	6.370***	5.115***	6.530***
	(0.044)	(0.190)	(0.108)	(0.097)	(0.124)	(0.072)
# Lagged Close Races	0.198***	0.250***	0.239***	0.171***	0.268***	0.099***
	(0.005)	(0.019)	(0.012)	(0.013)	(0.013)	(0.008)
% Itemizers	-138.403***	-114.902***	-188.723***	-49.794**	-176.858***	-36.512**
	(8.048)	(24.815)	(17.689)	(21.076)	(13.883)	(18.484)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

Table G.5: First-Stage Estimates of Equation (1.14) (Dependent Variable: Log Ads)

	All	Arts	Education	Health	Human Services	Other
# Races	0.081***	0.129***	0.091***	0.058***	0.160***	0.045***
	(0.003)	(0.013)	(0.008)	(0.006)	(0.009)	(0.004)
Avg. Cost per Minute	-130971.429***	-158436.003***	-145910.705***	-142638.820***	-173380.401***	-113537.342***
	(3019.261)	(11816.550)	(8358.010)	(6578.654)	(7633.360)	(5396.493)
Log Personal Income/1000	1870.285***	1822.380***	1667.796***	2048.405***	1867.190***	1663.247***
	(9.946)	(33.306)	(25.913)	(24.200)	(18.020)	(20.281)
Log Population/1000	1134.564***	1181.846***	1610.543***	878.927***	1048.338***	942.044***
	(30.216)	(95.596)	(73.387)	(75.198)	(52.638)	(55.766)
Fundraisers' Salaries	2.218***	2.306***	3.055***	0.429	3.359***	1.998***
	(0.120)	(0.410)	(0.268)	(0.310)	(0.208)	(0.239)
% Follow News	3.810***	3.571***	4.955***	3.565***	2.874***	4.332***
	(0.080)	(0.298)	(0.191)	(0.181)	(0.177)	(0.177)
# Lagged Close Races	-0.553***	-0.770***	-0.514***	-0.439***	-0.902***	-0.431***
	(0.014)	(0.055)	(0.027)	(0.034)	(0.038)	(0.024)
% Itemizers	-7070.420***	-6852.849***	-6590.590***	-7184.540***	-6872.307***	-6536.768***
	(27.009)	(93.531)	(73.286)	(67.886)	(51.234)	(56.346)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. All coefficients scaled by 100.

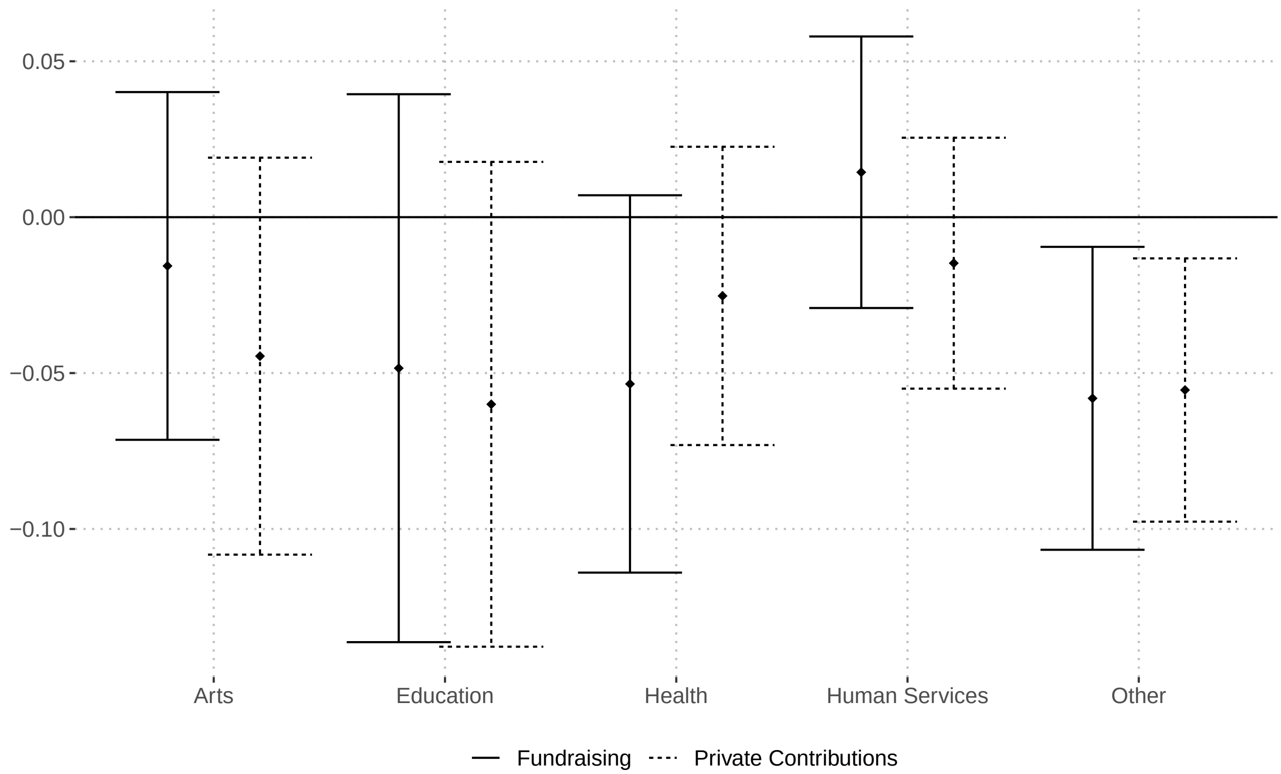
APPENDIX H

Robustness: Number of Uncontested Races

Table H.1: Average Effect on Charitable Fundraising and Contributions

	Fundraising	Contributions	Gov. Grants	Priv. Contrib.
Log Political Contrib.	-0.033***	-0.053***	-0.041**	-0.035***
	(0.012)	(0.009)	(0.018)	(0.011)
Log Personal Income/1000	1.162***	1.832***	2.822***	1.364***
	(0.225)	(0.166)	(0.268)	(0.187)
Log Population/1000	0.238	-0.227	0.084	0.309
	(0.465)	(0.330)	(0.499)	(0.374)
Fundraisers' Salaries	-0.000	0.002***	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	0.005***	0.006***	0.008***	0.003*
	(0.002)	(0.001)	(0.002)	(0.002)
% Itemizers	-0.318***	-0.204***	-0.107	-0.176**
	(0.080)	(0.061)	(0.100)	(0.071)
Observations	273,774	520,447	218,834	487,133
No. Groups	39,295	67,779	32,387	64,444
First-Stage F-Stat	5,406.809	5,934.061	2,423.826	5,781.210
Within R-squared	0.005	0.003	0.011	0.001

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.



Notes: Error bars represent 95% confidence intervals. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Figure H.1: Average Effect on Charitable Fundraising and Contributions, by Sector

Table H.2: Estimated Components of Fundraising Response

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	40.041***	24.473***	28.249***	23.348***	46.265***	56.873***
	(2.469)	(4.921)	(5.415)	(3.993)	(5.23)	(5.669)
$\frac{\partial Y}{\partial P}$	0.282	-0.155	2.055	0.495	-0.367	0.292
	(0.269)	(0.513)	(5.048)	(0.455)	(0.527)	(0.594)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.110***	-0.048	-0.104**	-0.070*	-0.058	-0.187***
	(0.026)	(0.034)	(0.051)	(0.043)	(0.083)	(0.067)
Observations	203,317	25,638	35,919	26,886	67,786	47,088
No. Groups	26,341	3,285	4,644	3,500	8,753	6,159

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

Table H.3: Political Ads Account for One-Quarter of Overall Effect

	All	Arts	Education	Health	Human Services	Other
	Panel A: Unconditional Elasticity					
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.047***	-0.095**	-0.071	-0.042	-0.019	-0.061**
	(0.015)	(0.046)	(0.057)	(0.033)	(0.029)	(0.028)
	Panel B: Conditional Elasticity					
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.033***	-0.037	-0.039	-0.045	-0.022	-0.055**
	(0.012)	(0.033)	(0.042)	(0.036)	(0.019)	(0.026)
$\frac{\partial \ln(Y)}{\partial \ln(A)}$	-0.127***	-0.282**	-0.275	-0.153	0.012	-0.173
	(0.049)	(0.120)	(0.183)	(0.150)	(0.059)	(0.108)
	Panel C: Difference					
$\Delta\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.014***	-0.058**	-0.033	.004	.003	-0.006
	(0.005)	(0.024)	(0.023)	(0.007)	(0.017)	(0.007)
Observations	364,866	36,003	64,279	60,420	123,129	81,035
No. Groups	63,509	6,103	11,143	10,610	21,658	13,995

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Additional tables available upon request.

Table H.4: Elasticities of Charitable Fundraising and Contributions by Ideology

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Political Contrib.	0.519	0.333	-0.337*	0.614	-5.437	0.255	-0.397**	-1.916
	(0.415)	(0.371)	(0.178)	(0.471)	(29.033)	(0.578)	(0.193)	(4.167)
Log Personal Income/1000	-2.538	-2.566	3.888**	-4.997	45.619	-1.755	4.700***	16.592
	(3.473)	(3.415)	(1.657)	(4.087)	(236.208)	(5.143)	(1.737)	(34.555)
Log Population/1000	3.082	3.528	-1.821	5.032*	-34.515	2.831	-1.718	-10.898
	(2.787)	(2.972)	(1.145)	(2.907)	(185.040)	(4.214)	(1.241)	(25.334)
Fundraisers' Salaries	0.006	0.005	-0.005***	0.005*	-0.042	-0.001	-0.002	-0.004
	(0.007)	(0.004)	(0.002)	(0.003)	(0.235)	(0.003)	(0.001)	(0.013)
% Follow News	0.013	0.001	0.006**	0.004	-0.120	0.000	0.005*	-0.043
	(0.008)	(0.005)	(0.003)	(0.004)	(0.668)	(0.007)	(0.003)	(0.092)
# Lagged Close Races	-0.007	-0.003	0.002*	-0.008	0.091	-0.003	0.003**	0.033
	(0.006)	(0.004)	(0.001)	(0.006)	(0.488)	(0.008)	(0.002)	(0.071)
% Itemizers	-0.303	0.213	-0.495**	-0.151	4.692	0.178	-0.304	1.769
	(0.296)	(0.235)	(0.225)	(0.147)	(26.559)	(0.234)	(0.198)	(4.012)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710
First-Stage F-Stat	2.209	1.507	12.954	2.407	0.035	0.670	14.290	0.236
Within R-squared	-0.027	-0.004	-0.008	-0.041	-2.312	-0.005	-0.016	-0.270

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table H.5: Elasticities of Charitable Fundraising and Contributions by Ideology and Party

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Share Rep. Contrib.	0.542	-0.489	0.388*	0.751	1.968**	2.219*	0.294	-0.224
	(1.213)	(1.186)	(0.200)	(0.743)	(0.965)	(1.140)	(0.196)	(0.558)
Log Share Dem. Contrib.	0.501**	0.344	0.087	0.364**	0.296	-0.142	0.188*	0.281**
	(0.221)	(0.266)	(0.085)	(0.179)	(0.225)	(0.285)	(0.096)	(0.143)
Log Personal Income/1000	4.687	-2.387	2.881***	4.490	11.547**	13.101**	2.749***	-0.493
	(6.421)	(6.949)	(1.101)	(4.150)	(5.053)	(6.509)	(1.066)	(3.020)
Log Population/1000	-3.924	4.479	-2.786*	-3.938	-13.797**	-14.086*	-1.518	2.260
	(9.220)	(8.243)	(1.566)	(5.365)	(7.010)	(7.852)	(1.518)	(3.845)
Fundraisers' Salaries	-0.003	0.003	-0.003***	0.000	-0.002	-0.002	-0.001	0.002
	(0.006)	(0.003)	(0.001)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)
% Follow News	0.003	-0.004	0.003	0.003	0.004	0.006	0.001	-0.003
	(0.006)	(0.008)	(0.002)	(0.005)	(0.005)	(0.006)	(0.002)	(0.003)
# Lagged Close Races	0.001	0.000	0.000***	0.001	0.002*	0.003*	0.000***	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
% Itemizers	0.275	-0.025	0.059	0.085	0.916	1.249**	0.196	-0.146
	(0.712)	(0.482)	(0.117)	(0.293)	(0.631)	(0.580)	(0.123)	(0.303)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710
S-W F-Stat: Rep. Contrib	32.515	32.527	1,269.511	101.179	68.526	46.369	1,929.875	189.469
S-W F-Stat: Dem. Contrib	89.594	62.348	3,169.834	135.956	110.313	79.264	3,918.480	151.702
Within R-squared	0.001	-0.006	0.013	-0.009	-0.054	-0.085	0.005	-0.002
p-val $\beta_D = \beta_R$	0.973	0.436	0.197	0.555	0.076	0.024	0.642	0.283

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

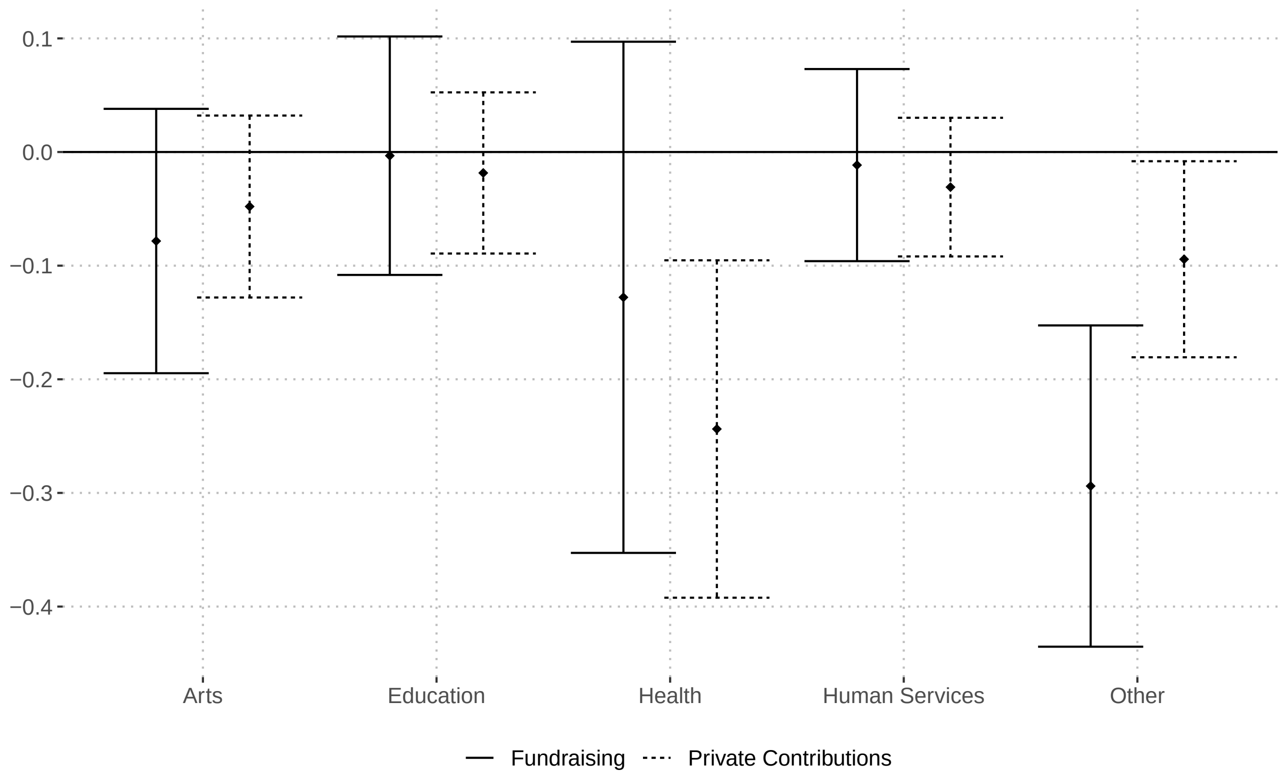
APPENDIX I

Robustness: Omission of Schedule R Filers

Table I.1: Average Effect on Charitable Fundraising and Contributions

	Fundraising	Contributions	Gov. Grants	Priv. Contrib.
Log Political Contrib.	-0.105***	-0.064***	-0.021	-0.072***
	(0.027)	(0.016)	(0.023)	(0.019)
Log Personal Income/1000	1.608***	1.824***	2.584***	1.515***
	(0.354)	(0.221)	(0.328)	(0.252)
Log Population/1000	0.523	-0.340	-0.244	0.207
	(0.590)	(0.380)	(0.591)	(0.432)
Fundraisers' Salaries	-0.002	0.002***	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	0.001	0.002*	0.008***	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)
% Itemizers	-0.094	-0.006	-0.074	0.061
	(0.081)	(0.058)	(0.095)	(0.069)
# Lagged Close Races	0.001***	0.001***	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	196,381	357,438	146,127	341,049
No. Groups	29,396	47,867	22,447	46,309
First-Stage F-Stat	333.582	498.292	237.261	472.695
Within R-squared	0.004	0.003	0.009	0.001

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.



Notes: Error bars represent 95% confidence intervals. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Figure I.1: Average Effect on Charitable Fundraising and Contributions, by Sector

Table I.2: Estimated Components of Fundraising Response

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	45.369***	24.473***	34.139***	26.676***	51.876***	62.525***
	(3.099)	(5.431)	(6.12)	(4.582)	(6.901)	(7.197)
$\frac{\partial Y}{\partial P}$	-0.017	-0.223	0.019	-0.650	-0.965	1.460**
	(0.291)	(0.614)	(0.783)	(0.692)	(0.622)	(0.736)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.279***	-0.161	-0.056	-0.236	0.046	-0.802***
	(0.077)	(0.109)	(0.106)	(0.221)	(0.179)	(0.212)
Observations	143,046	20,668	23,001	16,287	48,490	34,600
No. Groups	19,909	2,785	3,271	2,287	6,716	4,850

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

Table I.3: Political Ads Account for Majority of Overall Effect

	All	Arts	Education	Health	Human Services	Other
			Panel A: Unconditional Elasticity			
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.078***	-0.070	-0.013	-0.212***	-0.041	-0.102**
	(0.019)	(0.047)	(0.046)	(0.061)	(0.032)	(0.041)
			Panel B: Conditional Elasticity			
$\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.026*	0.019	0.033	-0.063	-0.042*	-0.058**
	(0.014)	(0.036)	(0.038)	(0.042)	(0.025)	(0.026)
$\frac{\partial \ln(Y)}{\partial \ln(A)}$	-0.060***	-0.082**	-0.070	-0.218***	0.001	-0.059
	(0.018)	(0.037)	(0.055)	(0.071)	(0.024)	(0.043)
			Panel C: Difference			
$\Delta\frac{\partial \ln(Y)}{\partial \ln(P)}$	-0.052***	-0.089**	-0.046	-0.149***	.001	-0.043
	(0.016)	(0.040)	(0.036)	(0.046)	(0.028)	(0.032)
Observations	256,308	29,761	44,319	33,039	89,077	60,112
No. Groups	45,382	5,127	7,934	5,925	15,826	10,570

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Additional tables available upon request.

Table I.4: Elasticities of Charitable Fundraising and Contributions by Ideology

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Political Contrib.	-0.212*	-0.176	-0.085**	-0.084	-0.111*	-0.109	-0.073**	-0.039
	(0.119)	(0.183)	(0.035)	(0.055)	(0.057)	(0.106)	(0.029)	(0.031)
Log Personal Income/1000	3.495***	1.568	1.698***	0.580	1.939**	1.143	1.716***	0.946**
	(1.307)	(1.956)	(0.489)	(0.657)	(0.815)	(1.195)	(0.400)	(0.391)
Log Population/1000	-0.868	3.040	-0.458	1.811*	-0.536	-0.385	0.145	0.774
	(2.027)	(2.242)	(0.821)	(1.044)	(1.518)	(1.537)	(0.678)	(0.657)
Fundraisers' Salaries	-0.000	0.000	-0.005***	0.001	-0.001	-0.001	-0.001	0.003***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
% Follow News	-0.002	0.000	0.002	-0.004	0.003	-0.002	0.001	-0.004
	(0.007)	(0.006)	(0.003)	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)
# Lagged Close Races	0.004*	0.003	0.001***	0.002**	0.002	0.002	0.001***	0.001
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
% Itemizers	0.399	0.094	-0.141	0.072	-0.194	0.423*	0.091	0.118
	(0.321)	(0.239)	(0.118)	(0.150)	(0.263)	(0.231)	(0.101)	(0.126)
Observations	18,729	20,239	83,103	74,310	30,332	32,067	114,270	164,380
No. Groups	2,813	2,979	12,005	11,599	4,107	4,323	15,409	22,470
First-Stage F-Stat	17.845	9.147	282.280	61.427	46.659	18.461	301.187	162.759
Within R-squared	0.003	0.004	0.018	-0.000	0.002	0.003	0.008	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Table I.5: Elasticities of Charitable Fundraising and Contributions by Ideology and Party

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Share Rep. Contrib.	0.648*	1.148*	0.266**	0.416*	0.480*	0.584	0.351***	0.246
	(0.363)	(0.658)	(0.135)	(0.243)	(0.261)	(0.503)	(0.114)	(0.161)
Log Share Dem. Contrib.	0.361	1.114**	0.812***	0.306	0.527	0.527	0.383**	0.109
	(0.421)	(0.529)	(0.223)	(0.233)	(0.336)	(0.518)	(0.186)	(0.156)
Log Personal Income/1000	5.196**	6.240	2.537***	2.157	3.550**	3.303	2.965***	1.936**
	(2.174)	(3.876)	(0.820)	(1.457)	(1.592)	(2.868)	(0.687)	(0.933)
Log Population/1000	-4.599	-3.480	-1.807	-0.644	-3.255	-3.476	-1.846*	-0.631
	(3.445)	(4.854)	(1.270)	(2.006)	(2.409)	(3.582)	(1.049)	(1.267)
Fundraisers' Salaries	-0.001	-0.002	-0.007***	0.000	-0.002	-0.002	-0.002*	0.003**
	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
% Follow News	0.001	-0.002	-0.002	-0.002	0.003	-0.003	-0.001	-0.003
	(0.007)	(0.007)	(0.003)	(0.004)	(0.006)	(0.006)	(0.003)	(0.003)
# Lagged Close Races	0.002	0.003**	0.001***	0.001**	0.001	0.002	0.001***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
% Itemizers	0.614	0.687*	0.084	0.243	0.041	0.712*	0.319***	0.207
	(0.405)	(0.410)	(0.126)	(0.200)	(0.344)	(0.392)	(0.113)	(0.163)
Observations	18,729	20,239	83,103	74,310	30,332	32,067	114,270	164,380
No. Groups	2,813	2,979	12,005	11,599	4,107	4,323	15,409	22,470
S-W F-Stat: Rep. Contrib	130.179	96.024	1,285.638	316.499	221.601	129.939	1,250.949	842.738
S-W F-Stat: Dem. Contrib	312.157	150.832	1,249.693	840.804	536.950	254.162	1,752.352	2,413.241
Within R-squared	0.003	-0.019	0.007	-0.002	-0.003	-0.002	0.007	-0.000
p-val $\beta_D = \beta_R$	0.395	0.940	0.028	0.568	0.844	0.860	0.870	0.238

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

APPENDIX J

The Role of Ideological Similarity

J.1 Theoretical Framework

As discussed in Section 1.6, the political environment is a function of political contributions. In a two-party system, contributions to a left-oriented party have an opposite-signed effect on the political environment than contributions to a right-oriented party ($\frac{\partial \alpha(P_L,P_R)}{\partial P_L} = -\frac{\partial \alpha(P_L,P_R)}{\partial P_R}$). It follows that the signs of the elasticities of charitable giving and fundraising to political contributions should depend on which political party receives this financial support.

If this is the case, then charitable contributions should fall in donations made to ideologically similar politicians, and may rise in contributions made to ideologically dissimilar politicians. This story is complicated by the fact that, in the United States, the two major political parties have acquired reputations as parties of "big" or "small" government. This differential willingness to spend across political parties implies that when the party of "big government" is in power, a given charitable donor may expect aggregate public good provision to increase, and the reverse is true when the party of "small government" is in power. Changes to the expected size of public good provision can affect donors' contributions even to apolitical charities, as public provision has been shown to partially crowd out private charitable giving.

This section further explores how the relationship between political and charitable giving varies according to the political party which benefits from these political donations. If ideology only matters insofar as it affects the expected amount of public good provision, then charitable giving should rise in contributions made to Republicans, and fall in contributions made to Democrats, regardless of the ideological lean of the organization. If donors view ideologically similar politicians and charities as substitutes, then giving to left-leaning organizations should fall in contributions made to Democrats, and giving to right-leaning organizations should fall in contributions made to Republicans. The opposite signs should obtain for these relationships if donors look at ideologically similar politicians and charities as complements. Finally, a "rage donation" motive will be detected if the charity's contributions rise in greater financial support for parties of the opposite ideology.

J.2 Empirical Strategy

To explore the role of ideological similarity or dissimilarity in determining this relationship, the following equation is estimated:

$$\ln(Y_{it(i)}) = \sum_{\rho} \beta_\rho \ln\left(\frac{P_{\rho m(i)t(i)}}{P_{m(i)t(i)}}\right) + \beta_x X_{it(i)} + \varepsilon_{it(i)} \tag{J.1}$$

Here, $\rho \in \{\text{D,R}\}$ indexes the political party which receives these contributions. $\frac{P_{\rho m(i)t(i)}}{P_{m(i)t(i)}}$ reflects the share of political contributions made by donors in the charity's market, during its fiscal year, which accrue to the Democratic or Republican parties, respectively.[1] The set of instruments used to estimate (J.1) will include the number of races with incumbents, and the difference between the number of races with Democratic incumbents and the amount of races with Republican incumbents.[2] The relevance of these instruments derives from the incumbency advantage in political fundraising (*Gelman and King* (1990); *Cox and Morgenstern* (1993); *Carson et al.* (2007); *Fouirnaies and Hall* (2014)).

[1]Shares do not sum to unity, because not all candidates fall into one of these two groups, and not all contributions made to third-party PACs will accrue to Democrats or Republicans in an observable way. The FEC may classify a political action committee as "Other" when it is not officially affiliated with a particular party or candidate. However, spending by these PACs is observable from the a different FEC data file, entitled "Contributions from committees to candidates and independent expenditures". This file enables calculation of the shares of each PAC's expenditure going to Democrats, Republicans, or other recipients within each two-year election cycle. Let d represent the share of a PAC's expenditures going to Democrats, and r represent the share of a PAC's expenditures going to Republicans. When individuals make a contribution of $\$x$ to this PAC during this two year cycle, this is recorded as a contribution of $\$dx$ to Democrats and $\$rx$ to Republicans, made on the date of the individual's contribution.

[2]The CQ Voting and Elections data includes information on the incumbency status and partisan affiliation of the challengers, which is used to construct these of instruments.

Specification (J.1) will also be estimated on each ideological subsample. If political donors view ideologically similar politicians and charities as substitutes, the coefficient β_D should be negative among left-leaning charities, and the coefficient β_R should be negative among right-leaning charities.

J.3 Results

Estimates are presented in Table J.1 Increases in relative financial support for Republicans tend to raise fundraising by left-leaning charities, as well as contributions received by these charities, while increases in relative financial support for Democrats tend to raise both fundraising and private contributions at right-leaning charities. These relationships are positive and statistically significant, suggesting that gifts to ideologically dissimilar politicians and charities may be complements. This may be consistent with the phenomenon of "rage donations," in which voter-donors express political opposition by throwing financial support behind organizations working at cross purposes to the government. As the same individuals are unlikely to support both right-leaning charities and left-leaning politicians, or vice versa, these results also attest to the importance of spillover effects of political donors' giving on others' charitable contributions.

However, these precise estimates of the relationship between ideologically dissimilar politicians and charities are not statistically distinguishable from the estimates of the relationship between ideologically similar politicians and charities. For all but one specification, it is not possible to reject a null hypothesis that the effect of political contributions on charitable giving and fundraising is the same regardless of which political party receives support.

This section therefore provides some suggestive evidence that the relationship between political and charitable contributions is ideologically motivated, but the exact nature of this relationship remains unclear. Apolitical organizations are less affected by political contributions than left-leaning or politically moderate groups, and gifts to ideologically dissimilar politicians increase fundraising and private contributions at charities on both the left and the right, but it is not possible to say whether gifts to ideologically similar and dissimilar politicians affect these charities in different ways.

Table J.1: Elasticities of Charitable Fundraising and Contributions by Ideology and Party

	Log Fundraising				Log Private Contributions			
	Left	Right	Center	Apolitical	Left	Right	Center	Apolitical
Log Share Rep. Contrib.	0.554**	0.484	0.054	0.289	0.448**	0.526	0.388***	0.105
	(0.280)	(0.377)	(0.101)	(0.206)	(0.222)	(0.330)	(0.097)	(0.142)
Log Share Dem. Contrib.	0.360	0.965**	0.837***	0.326	0.435	0.884*	0.308	-0.013
	(0.373)	(0.453)	(0.217)	(0.227)	(0.333)	(0.466)	(0.195)	(0.153)
Log Personal Income/1000	4.732***	3.042	1.407**	1.952	3.732***	3.242*	3.262***	1.275
	(1.677)	(2.295)	(0.597)	(1.240)	(1.345)	(1.898)	(0.578)	(0.828)
Log Population/1000	-4.007	-2.075	-0.469	-0.675	-3.075	-2.352	-2.157**	0.028
	(2.681)	(2.987)	(0.956)	(1.718)	(2.071)	(2.464)	(0.884)	(1.139)
Fundraisers' Salaries	-0.002	0.001	-0.005***	0.001	-0.000	-0.004	-0.001	0.002*
	(0.004)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
% Follow News	0.004	-0.004	-0.001	0.000	0.003	-0.007	0.001	0.000
	(0.006)	(0.006)	(0.002)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
# Lagged Close Races	0.001*	0.002**	0.001***	0.001	0.001	0.001*	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
% Itemizers	0.266	0.406	-0.076	-0.075	0.019	0.586**	0.240**	-0.029
	(0.308)	(0.272)	(0.101)	(0.158)	(0.278)	(0.282)	(0.102)	(0.138)
Observations	26,560	27,821	122,888	96,505	45,357	45,351	176,554	219,871
No. Groups	3,817	3,959	16,875	14,644	5,954	5,913	22,867	29,710
S-W F-Stat: Rep. Contrib	198.016	186.927	1,955.321	586.741	326.946	218.139	2,746.353	1,129.669
S-W F-Stat: Dem. Contrib	480.419	273.170	1,408.711	1,275.837	805.611	419.384	2,324.740	3,392.782
Within R-squared	0.002	-0.007	-0.000	-0.001	-0.001	-0.006	0.003	0.000
p-val $\beta_D = \beta_R$	0.523	0.229	0.002	0.847	0.956	0.273	0.708	0.311

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

APPENDIX K

Components of Fundraising Response, Including Sometimes-Fundraisers

The below table reproduces Table 1.5, including organizations observed reporting zero fundraising expenses in some, but not all, periods.

Table K.1: Estimated Components of Fundraising Response

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	127.404***	56.827***	103.78***	122.113***	106.573***	197.458***
	(7.946)	(11.578)	(20.649)	(18.901)	(11.965)	(20.05)
$\frac{\partial Y}{\partial P}$	0.490	-0.290	0.758	1.040	-0.838	1.976**
	(0.414)	(0.754)	(1.863)	(1.145)	(0.685)	(0.975)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.806***	-0.217	-0.491	-1.647***	0.134	-2.312***
	(0.177)	(0.205)	(0.353)	(0.603)	(0.329)	(0.580)
Observations	252,985	30,516	44,581	35,536	85,292	57,060
No. Groups	39,131	4,440	6,933	5,774	13,246	8,738

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

Table K.2: Estimated Components of Fundraising Response, Controlling for Liabilities to Assets Ratio

	All	Arts	Education	Health	Human Services	Other
$\frac{\partial Y}{\partial F}$	127.281***	56.359***	103.135***	122.985***	103.024***	197.453***
	(7.932)	(11.537)	(20.377)	(18.865)	(11.355)	(20.046)
$\frac{\partial Y}{\partial P}$	0.490	-0.298	0.759	1.058	-0.833	1.984**
	(0.414)	(0.750)	(1.860)	(1.149)	(0.673)	(0.976)
$\frac{\partial^2 Y}{\partial F \partial P}$	-0.806***	-0.215	-0.488	-1.660***	0.130	-2.313***
	(0.177)	(0.203)	(0.350)	(0.607)	(0.316)	(0.581)
Observations	252,953	30,515	44,574	35,536	85,280	57,048
No. Groups	39,125	4,440	6,932	5,774	13,242	8,737

Notes. *p<0.1; **p<0.05; ***p<0.01. These estimates are produced using the formulae outlined in Equations (1.8), (1.9), and (1.10). The underlying equations used to produce these estimates include a control for the ratio of total liabilities to assets on the charity's balance sheet at the beginning of its fiscal year. Standard errors are calculated via the delta method. All financial variables are deflated to constant 2015 dollars.

Additional tables available upon request.

APPENDIX L

Intertemporal Effects

Political contributions are tied to the election cycle. This creates a sense of urgency in donating to a political campaign. It is unlikely that the decision to give to charity involves such urgency. It is therefore possible that political donors substitute away from charity and towards giving to politicians within a period, but end up making up for any shortfall in charitable contributions by giving more to charity in the next period. If this were the case, then current-period charitable contributions would fall in current-period political contributions, but rise in lagged political contributions. If the coefficient on lagged political contributions is positive and sufficiently large, then the social cost created by political contributions may actually be negligible. This possibility is explored in Table L.1.

Table L.1 presents the results of estimating the following specification:

$$\ln(Y_{it(i)}) = \beta_p \ln(P_{m(i)t(i)}) + \beta_{lp} \ln(P_{m(i),t(i)-1}) + \beta_x X_{it(i)} + \varepsilon_{it(i)} \tag{L.1}$$

where outcome variables include both charitable fundraising and charitable giving.

Table L.1: Average Intertemporal Effects on Charitable Fundraising and Contributions

	Log Fundraising	Log Contributions	Log Gov. Grants	Log Priv. Contrib.
Log Political Contrib.	-0.169***	-0.120***	0.027	-0.135***
	(0.060)	(0.037)	(0.047)	(0.044)
L.Log Political Contrib.	-0.099**	-0.069***	0.020	-0.073***
	(0.039)	(0.023)	(0.029)	(0.028)
Log Personal Income/1000	2.217***	2.206***	2.250***	2.024***
	(0.498)	(0.313)	(0.416)	(0.365)
Log Population/1000	-0.924	-0.849*	0.722	-0.533
	(0.670)	(0.455)	(0.639)	(0.524)
Fundraisers' Salaries	-0.001	0.002**	0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
% Follow News	-0.007*	-0.002	0.011***	-0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
# Lagged Close Races	0.001***	0.001**	-0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
% Itemizers	0.252	0.249**	-0.275*	0.308**
	(0.174)	(0.124)	(0.156)	(0.146)
Observations	268,467	509,619	214,798	476,853
No. Groups	39,149	67,685	32,219	64,344
First-Stage F-Stat	177.267	247.212	166.481	226.366
Within R-squared	-0.000	0.002	0.009	-0.001

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

Note that in Table L.1, charitable fundraising and private contributions fall in both current-period political contributions and lagged political contributions. This result confirms that losses in private charity experienced in the current period persist to the subsequent period. It further suggests that political and charitable contributions may be intertemporal substitutes, as well as substitutes in the current period. This implies that static estimates of the relationship between political and charitable giving actually understate the effect of political contributions on private charity.

APPENDIX M

Heterogeneity by Size

This section addresses the possibility that the relationship between political and charitable giving depends on the size of the charitable organization. As noted in Section 1.4.1, the results presented in this paper pertain to relatively large organizations. Examining how the coefficient of interest varies by the size of these organizations may provide some insight into the extent to which these results may be applicable to smaller charities.

Table M.1: Average Effects on Charitable Fundraising and Contributions, by Size

	Log Fundraising	Log Contributions	Log Gov. Grants	Log Priv. Contrib.
Log Political Contrib. × Q1	-0.044**	-0.045***	-0.008	-0.043***
	(0.019)	(0.012)	(0.016)	(0.014)
Log Political Contrib. × Q2	-0.067***	-0.076***	-0.026	-0.078***
	(0.019)	(0.013)	(0.018)	(0.015)
Log Political Contrib. × Q3	-0.085***	-0.064***	0.011	-0.074***
	(0.021)	(0.014)	(0.018)	(0.017)
Log Political Contrib. × Q4	-0.097***	-0.076***	0.007	-0.094***
	(0.022)	(0.016)	(0.024)	(0.019)
Log Political Contrib. × Q5	-0.116***	-0.075***	0.031	-0.091***
	(0.026)	(0.022)	(0.037)	(0.024)
Observations	273,774	520,447	218,834	487,133
No. Groups	39,295	67,779	32,387	64,444
First-Stage F-Stat: Q1	783.015	1,069.688	1,108.412	1,002.635
First-Stage F-Stat: Q2	779.433	1,018.247	755.530	954.193
First-Stage F-Stat: Q3	799.587	1,019.144	649.351	958.777
First-Stage F-Stat: Q4	839.798	1,035.635	634.336	980.837
First-Stage F-Stat: Q5	973.581	1,128.414	718.384	1,069.361
Within R-squared	0.004	0.003	0.009	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars. "First-Stage F-Stat: Q1" refers to the first-stage F-statistic for the interaction of the instrument with the indicator representing the first quintile of the distribution of mean assets; similar definitions apply for quintiles 2 through 5.

The analysis in this section proceeds by dividing charities into five quintiles, based on the mean amount of assets a charity holds during the sample period. Indicators are defined to represent each quintile, Q1 through Q5. These indicators are interacted with both the natural log of political contributions and its instrument, the number of political races. Table M.1 presents estimates of the following specification:

$$\ln(Y_{it(i)}) = \sum_{k=1}^{5} \Big\{ \beta_{p,k} \ln(P_{m(i)t(i)}) \times \mathbf{1}(Q == k) \Big\} + \beta_x X_{it(i)} + \varepsilon_{it(i)} \tag{M.1}$$

where $X_{it(i)}$ is defined as in Equation (1.1). The results reveal that the elasticities of charitable fundraising and contributions to political contributions increase in absolute value with the size of the charity. This gradient is fairly steep when charitable fundraising is taken as the outcome variable: organizations in the first quintile are significantly less sensitive to political contributions than organizations in the second or third quintiles ($p = 0.0536$ and $p = 0.0011$, respectively). Charities in the second quintile are in turn less sensitive to political contributions than those in the fourth or fifth quintiles ($p = 0.0091$ and $p = 0.0002$, respectively). Charities in the third quintile are also more sensitive than those in the fifth quintile ($p = 0.0163$), but those in the fourth quintile are only marginally less sensitive than the largest organizations ($p = 0.1087$).

When private charitable contributions are the outcome, a weaker form of this gradient remains. The smallest charities remain much more sensitive to political contributions than those in all other quintiles;[1] but only one pairwise comparison between coefficients estimated for the largest four quintiles reveals a statistically significant difference.

These estimates reveal that political contributions do reduce charitable fundraising and private contributions for the smallest 20% of charities in this sample, although this relationship is weaker than the one that holds for larger charities. It follows that Form 990-EZ filers, which are too small to be included in the present analysis, likely lose some charitable contributions to political giving as well. This is a promising direction for future research.

[1]The p-values for Wald tests of the difference in coefficients between $\beta_{p,1}$ and $\beta_{p,k}$ $\forall k \in \{2, 3, 4, 5\}$ are all less than or equal to 0.0016.

APPENDIX N

Effects on Net Private Contributions

This section presents additional results for Specification (1.1) using an alternative outcome variable: net private charitable contributions. This outcome variable represents private charitable contributions less charitable fundraising, which are the outcomes reflected in Columns 4 and 1 of Table 1.3, respectively. The results presented in Tables N.1 and N.2 are qualitatively consistent with those presented in Section 1.5. These estimates provide further evidence that the yield of a dollar of charitable fundraising falls in political contributions.

Table N.1: Average Effects on Net Private Contributions, by Sector

	All	Arts	Education	Health	Human Services	Other
Log Political Contrib.	-0.080***	-0.047	-0.069*	-0.143**	-0.065**	-0.076*
	(0.018)	(0.055)	(0.036)	(0.060)	(0.032)	(0.044)
Log Personal Income/1000	1.761***	0.411	0.991*	3.311***	1.869***	1.806***
	(0.238)	(0.648)	(0.515)	(0.750)	(0.417)	(0.524)
Log Population/1000	-0.083	-0.860	2.780***	-1.461	0.107	-1.283*
	(0.399)	(1.068)	(0.958)	(1.170)	(0.721)	(0.754)
Fundraisers' Salaries	0.001	0.002	0.003	-0.003	0.001	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
% Follow News	0.001	-0.003	-0.000	-0.000	-0.000	0.007**
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
# Lagged Close Races	0.001***	0.001	0.001	0.002**	0.001**	0.001*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
% Itemizers	-0.055	0.105	-0.201	-0.180	0.154	-0.348***
	(0.066)	(0.190)	(0.189)	(0.190)	(0.119)	(0.132)
Observations	476,109	47,111	83,544	78,231	160,586	106,634
No. Groups	64,054	6,100	11,196	10,722	21,942	14,093
First-Stage F-Stat	787.167	74.616	187.204	112.740	179.378	214.881
Within R-squared	0.000	0.002	0.001	-0.000	0.001	0.000

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

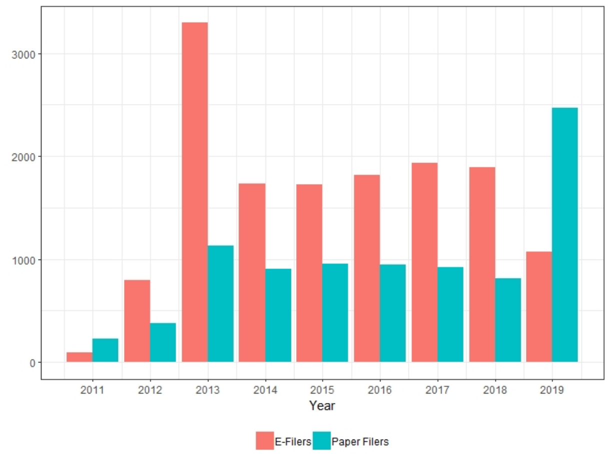
Table N.2: Average Effects on Net Private Contributions, by Ideology

	Left	Right	Center	Apolitical
Log Political Contrib.	-0.109*	-0.087	-0.107***	-0.016
	(0.057)	(0.070)	(0.028)	(0.032)
Log Personal Income/1000	2.374***	1.163	2.210***	0.849**
	(0.754)	(0.876)	(0.376)	(0.387)
Log Population/1000	-0.740	0.760	-0.300	0.601
	(1.340)	(1.356)	(0.611)	(0.633)
Fundraisers' Salaries	0.002	-0.002	-0.001	0.002**
	(0.003)	(0.003)	(0.001)	(0.001)
% Follow News	0.006	-0.002	0.004	-0.001
	(0.005)	(0.005)	(0.002)	(0.003)
# Lagged Close Races	0.001	0.001	0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
% Itemizers	-0.255	0.200	-0.061	-0.030
	(0.237)	(0.206)	(0.103)	(0.114)
Observations	44,221	44,317	172,341	215,230
No. Groups	5,924	5,888	22,729	29,513
First-Stage F-Stat	50.512	43.091	569.925	203.829
Within R-squared	0.001	0.002	0.003	0.000

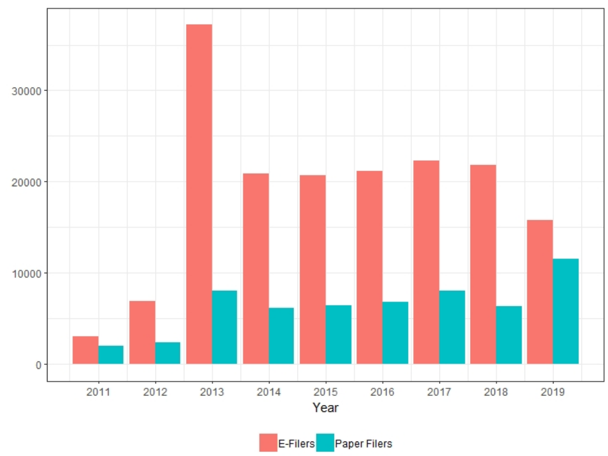
Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered by organization. All specifications include organization fixed effects and year fixed effects. All financial variables are deflated to constant 2015 dollars.

APPENDIX O

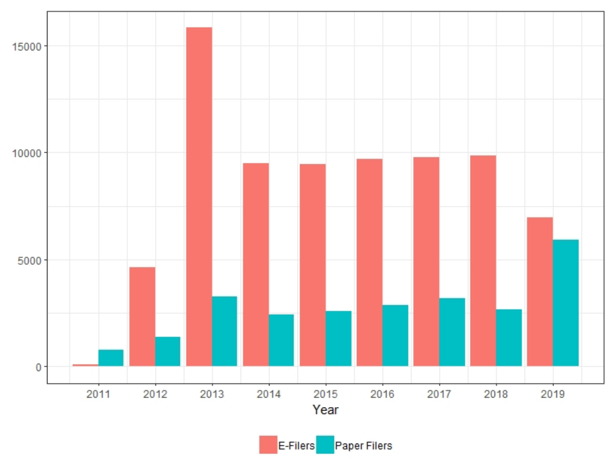
Selection into Electronic Filing



(a) Average Total Contributions (Thousands of Current Dollars)



(b) Average Total Assets (Thousands of Current Dollars)



(c) Average Total Functional Expenses (Thousands of Current Dollars)

Figure O.1: Comparison of E-Filers to Paper Filers, 2011-2019

APPENDIX P

Income Redistributions May Reduce Voluntary Public Good Provision

Bergstrom et al. (1986) proves an assertion that changes in the income distribution, which do not affect the aggregate income received by donors, will not reduce total provision of the public good. This assertion is found in Theorem 4. However, this prediction relies on several important modeling assumptions, which may not be well-suited to a setting in which charitable donors and recipients are drawn from disjoint parts of the income distribution. As previously mentioned, these results rely on two key assumptions: first, that all donors to the public good derive some utility from its provision, and second, that each donor believes their own gift will strictly increase total public good provision. Without these assumptions, the prediction that donors' contributions weakly increase in recipients' unmet needs will not obtain.

To see this, note that *Bergstrom et al.* (1986) specifies each agent's utility maximization problem as follows:

$$\begin{aligned} &\max_{x_i, g_i} u(x_i, G) \\ \text{s.t. } &x_i + g_i = y_i \\ &g_i \geq 0 \\ &G = \sum_i g_i \end{aligned}$$

Bergstrom et al. (1986) notes that donors who give $g_i > 0$ belong to a contributor set, C, whereas donors who give $g_i = 0$ are non-contributors. If donors in the contributor set derive no utility from G, then optimally they will allocate all income to private consumption, x_i. This implies that no donor belongs to the contributor set. This extreme outcome can be relaxed by allowing donors to derive warm-glow utility from their own donation, re-specifying the utility function as $u(x_i, g_i)$. In this case, per *Andreoni* (1990), the donor's optimal gift can be expressed as $g_i = f_i(y_i)$ and the utility functions of agents in both the contributor and non-contributor sets will no longer be interdependent. In Theorem 4 of *Bergstrom et al.* (1986), the authors assert that any redistribution of income which leave the incomes of the contributor set unchanged will weakly increase public good provision. This assertion does not go through in the case of perfectly egoistic utility. To see this, note that:

$$g_i = f_i(y_i)\ \forall i \in C$$
$$\phi_i(g_i) = y_i\ \forall i \in C$$

where $\phi_i(g_i)$ represents the inverse function of $f_i(y_i)$, and C denotes the contributor set. Suppose there are two contributors in the contributor set, contributing g_1 and g_2 respectively, such that total public good provision is given by $G = g_1 + g_2$. Does there exist some redistribution of their income such that $G' = g'_1 + g'_2 > G$?

First, note that:

$$G' = g'_1 + g'_2 = f_1(y'_1) + f_2(y'_2)$$
$$G = g_1 + g_2 = f_1(y_1) + f_2(y_2)$$

and suppose that this redistribution of income among the contributor set can be represented by taking $\Delta y_2 > 0$ from contributor 2 and giving it to contributor 1. Then $y'_1 = y_1 + \Delta y_2$ and $y'_2 = y_2 - \Delta y_2$. Then:

$$
\begin{aligned}
G' &< G \\
f_1(y_1') + f_2(y_2') &< f_1(y_1) + f_2(y_2) \\
f_1(y_1 + \Delta y_2) + f_2(y_2 - \Delta y_2) &< f_1(y_1) + f_2(y_2) \\
\frac{f_1(y_1 + \Delta y_2) - f_1(y_1)}{\Delta y_2} &< \frac{f_2(y_2) - f_2(y_2 - \Delta y_2)}{\Delta y_2} \\
\lim_{\Delta y_2 \to 0} \frac{f_1(y_1 + \Delta y_2) - f_1(y_1)}{\Delta y_2} &< \lim_{\Delta y_2 \to 0} \frac{f_2(y_2) - f_2(y_2 - \Delta y_2)}{\Delta y_2} \\
f_1'(y_1) &< f_2'(y_2)
\end{aligned}
$$

where the final inequality follows if both functions are differentiable. Then, if donors have purely egoistic preferences, a redistribution of income among this two-person contributor set can reduce total public good provision, if two conditions hold. First, both individuals' contributions must be increasing in their own income. Second, the contributor who loses income due to redistribution must have a greater marginal propensity to give to charity than the contributor who benefits from the redistribution. This can be accomplished easily, by setting $f_1(y_1) = 0.5\ln(y_1)$ and $f_2(y_2) = \ln(y_2)$. Then the results of Theorem 4 do not obtain for donors who derive no altruistic utility from the total level of public good provision.

If these same donors did derive altruistic utility from total G, but did not internalize the effect of their own gift on total public good provision ($\frac{\partial G}{\partial g_i} = 0$), then this altruistic term will simply fall out of the donor's first-order condition if G is either additively or multiplicatively separable from the rest of the donor's utility function. The remainder of the proof is unaffected, and G may fall following a redistribution of income, such that the total wealth of the contributor set remains unchanged.

This paper is concerned with one particular type of change in the income distribution, in which $\Delta y_2 = 0$, but where at least some agents who lie outside the contributor set experience $\Delta y_i < 0$. In this case, are the assumptions which underlie Theorem 4 of *Bergstrom et al.* (1986) appropriate? If so, then voluntary public good provision should weakly increase; if not, then voluntary public good provision may fall.

The first assumption is reasonable under one of two cases. In the first case, all private agents in the economy actively consume the same public good, regardless of whether these agents are donors or not. In the second case, this public good may generate an atmospheric externality which affects all private agents. For some types of charity, it may be appropriate to think of all agents as consuming the same public good; for example, anyone may visit an art museum, regardless of whether or not that person is a donor. However, there exists a whole suite of charitably provided goods and services which are unlikely to be consumed by the donors who fund these services. As an example, a donor to a homeless shelter is unlikely to spend the night in that establishment.

But what if these goods and services can be thought of as generating an atmospheric externality? By conceptualizing the public good in this way, previous models may appear appropriate ways of characterizing voluntary public good provision. However, unless the second assumption holds, and donors believe their gifts strictly increase total public good provision, then the prediction of the model will not go through. This assumption is not trivial, and it is not always employed by other models which include atmospheric externalities. These other works, e.g. *Sandmo* (1975), typically assume the agent does not internalize the effect of their own behavior, or equivalently, that the agent believes they are small. This approach has been implemented in more recent models of public good provision, such as *Duquette and Hargaden* (2021), to which the model in the present work is closely related.

APPENDIX Q

Results with Alternative Definitions of Income

This section presents results estimated using an alternative definition of income to the one employed in the main text. These tables use the log of personal income per capita at the state level. As this measure reflects income per capita which accrues to charitable recipients as well as donors, it is more closely correlated with food insecurity than the measure of income employed in the main text.[1] Consequently, the coefficients on the food insecurity variables displayed in Tables Q.1, Q.2, and Q.3 are measured with less precision than those presented in Tables 2.2, 2.3, 2.4. However, the coefficients are qualitatively similar to those presented in the main text.

[1]In this sample, the within-charity correlation between the food insecurity rate and the log of average household income above 500% of the poverty level is -0.04339. The within-charity correlation between the food insecurity rate and the log of personal income per capita is -0.07843.

Table Q.1: Average Effect of Food Insecurity on Charity Outcomes

	Fundraising			Private Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
Food Insecurity	0.006	0.006	0.002	0.001	0.001	-0.040
	(0.004)	(0.004)	(0.027)	(0.006)	(0.006)	(0.043)
Gini		0.137	0.030		-0.535	-1.766
		(0.476)	(0.983)		(0.740)	(1.693)
Food Insecurity × Gini			0.007			0.082
			(0.054)			(0.088)
Log Personal Income per Capita	2.288**	2.295**	2.291**	1.527**	1.503*	1.461*
	(1.064)	(1.078)	(1.086)	(0.773)	(0.791)	(0.806)
Pseudo-R^2	0.663	0.663	0.663	0.948	0.948	0.948
No. Obs	5029	5029	5029	6583	6583	6583
No. Charities	1071	1071	1071	1389	1389	1389

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the organization level. All specifications include organization and year fixed effects. All financial variables measured in millions of constant 2015 dollars.

Table Q.2: First Stage Specifications

	(1)	(2)	(3)
Food Insecurity	0.006	0.005	0.005
	(0.004)	(0.004)	(0.028)
Gini		0.150	0.135
		(0.479)	(0.999)
Food Insecurity × Gini			0.001
			(0.055)
IHS(Office Expenses)	0.187***	0.188***	0.188***
	(0.053)	(0.054)	(0.054)
Log Personal Income per Capita	1.800**	1.807**	1.806**
	(0.814)	(0.824)	(0.836)
Log Total Assets	0.177***	0.176***	0.176***
	(0.043)	(0.043)	(0.043)
Pseudo-R^2	0.663	0.663	0.663
No. Obs	5025	5025	5025
No. Charities	1071	1071	1071
χ^2 IHS(Office Expenses)	12.373	12.243	12.273
$p > \chi^2$	0.000	0.000	0.000
AIC	3259.523	3261.519	3263.519
BIC	3285.612	3294.130	3302.652

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors clustered at the organizational level. All specifications include organization and year fixed effects. All financial variables measured in millions of constant 2015 dollars.

Table Q.3: Direct and Indirect Effects of Food Insecurity on Contributions

	(1)	(2)	(3)	(4)	(5)	(6)
Log Fundraising	0.160	0.160	0.118	0.170	0.169	0.146
	[0.079, 0.421]	[0.078, 0.421]	[0.005, 0.282]	[0.010, 0.337]	[0.015, 0.354]	[0.003, 0.322]
Food Insecurity	-0.003	-0.003	-0.003	-0.003	-0.003	0.002
	[-0.017, 0.009]	[-0.017, 0.009]	[-0.017, 0.010]	[-0.016, 0.009]	[-0.082, 0.077	-0.069, 0.083]
Gini		-0.594		-0.613	-0.626	-0.446
		[-2.032, 0.738]		[-2.005, 0.849]	[-3.574, 2.575]	[-3.441, 2.460]
Log Fundraising × Food Insecurity			0.003			0.003
			[-0.005, 0.009]			[-0.005, 0.009]
Log Fundraising × Gini				-0.021	-0.021	-0.063
				[-0.182, 0.482]	[-0.197, 0.477]	[-0.242, 0.433]
Food Insecurity × Gini					0.001	-0.010
					[-0.163, 0.153]	[-0.165, 0.143]
Log Personal Income per Capita	1.319	1.300	1.268	1.293	1.296	1.256
	[-0.077, 2.668]	[-0.103, 2.715]	[-0.023, 2.749]	[-0.109, 2.759]	[-0.107, 2.785]	[-0.180, 2.766]
Log Total Assets	0.068	0.069	0.064	0.068	0.068	0.064
	[-0.045, 0.188]	[-0.045, 0.191]	[-0.047, 0.193]	[-0.045, 0.190]	[-0.040, 0.192]	[-0.048, 0.194]
$\hat{\nu}$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	[-0.015, -0.001]	[-0.015, -0.001]	[-0.014, -0.001]	[-0.017, -0.001]	[-0.017, -0.001]	[-0.016, -0.001]
No. Obs	4,397	4,397	4,397	4,397	4,397	4,397
No. Charities	990	990	990	990	990	990

Notes. *p<0.1; **p<0.05; ***p<0.01. Bias-corrected point estimates and 95% confidence intervals (reported in brackets) are produced using 500 bootstrap replications. Bootstrap standard errors clustered at the organizational level. All specifications include organization and year fixed effects. All financial variables reported in millions of constant 2015 dollars. $\hat{\nu}$ represents the standardized, generalized residual of the first-stage specification, which is included in estimation of the structural equation as part of the control function approach. For further details, see *Wooldridge* (2015).

APPENDIX R

Effect of COVID-19 on Charitable Fundraising and Total Revenues

Table R.1: Impact of COVID-19 on Fundraising and Revenue

	(1) Fundraising	(2) Revenue
Any Exposure · After	-0.169***	-0.339***
	(0.046)	(0.022)
Any Exposure	0.822***	1.121***
	(0.100)	(0.037)
After	0.158***	0.212***
	(0.033)	(0.020)
Constant	4.180***	13.311***
	(0.107)	(0.034)
Observations	341758	341758
R^2	0.004	0.040

Notes. *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function.

APPENDIX S

Hetereogeneity by COVID Intensity

S.0.1 COVID-19 Data

In order to examine heterogeneity by COVID-19 exposure, we use two different measures of severity: cumulative cases per capita and local foot traffic. The former is a measure of local prevalence of the virus, while the latter also captures state-level attitudes and lockdowns.

S.0.1.1 Community Mobility Reports

We use foot traffic as an alternative measure of the effect of COVID-19 on a community. These data come from Google's Community Mobility Reports, available at the state level beginning on February 15 2020. These measures reflect a percentage change in visits to retailers and recreational areas by Google users who have Location History enabled on their mobile devices[1]. This percentage change is calculated daily, relative to a baseline of the median value for the corresponding day of the week during a reference period of January 3 2020 through February 6 2020.

We accumulate these data in the following manner. Beginning on March 1 2020, we construct a daily difference from the percentage changes published by the Community Mobility Reports. We then take a cumulative sum of these daily differences, summing differences calculated from the beginning of March 2020 through the end of each month between March and November. The result

[1] Location is identified using the phone's GPS and connected WiFi devices, avoiding the compliance issues and recall bias that are common in self-reported travel history data. Although this feature can be turned off, some Google apps still store time-stamped location data: `https://apnews.com/article/north-america-science-technology-business-ap-top-news-828aefab64d4411bac257a07c1af0ecb`.

is a cumulative difference in foot traffic at retailers and recreational areas observed in state s by the end of month m, relative to the period just prior to the pandemic.

S.0.1.2 Cumulative Cases per Capita

Data on confirmed COVID-19 cases per day is collected from the New York Times[2], where the first reported case was in Washington state on January 21 2020. Our main specifications rely on cumulative counts at the state-level. Cases are recorded in the county in which they occurred[3], and historic data is updated to correct for errors. Undoubtedly, reporting errors still remain. However, given our interest in cumulative counts, any errors will become less significant over time. Lastly, population data are taken from Census estimates on July 1 2019.

One concern is that the updated data do not necessarily reflect the information that was being published at the time. In other words, donors and charities would have been responding to (mis)reported COVID-19 case and death counts, not the updated information we now have access to. In order to understand this difference, we compare the data available on April 7 2021 to those printed on May 6 2020[4]. Examining county-level information, COVID-19 case counts appear to be misreported in the May 6 data 2.5% of the time (where an observation is a county-day pair). This misreporting is not evenly distributed across states, with most states reporting accurately in May 2020. Where there is a discrepancy, it is mostly very small and due to early under-reporting.

Given that our specifications use cumulative counts, these discrepancies become less important over time.

S.0.2 Empirical Strategy

This specification investigates heterogeneity by COVID-19 intensity by making use of information on cumulative differences in foot traffic, or cumulative per-capita COVID-19 cases, at the state level. 60% of nonprofits end their fiscal year in December, and 28% file in June. Therefore, in these specifications, we hold filing month m fixed, focusing on comparisons between June filers and

[2]This is available via their `https://github.com/nytimes/covid-19-data`Github repository, and was collected on April 7 2021.

[3]Given that we are focused on state-level counts, the distinction between place of occurrence and place of residence is less important.

[4]We thank Michael Murto and Jon Denton-Schneider for providing these data.

charities which file between December and February[5]. Restricting attention to June filers allows us to examine whether charities located in states with greater differences in foot traffic, or higher cumulative case counts, were differentially affected by the pandemic. Thus, separately for each state, we run regressions of the form:

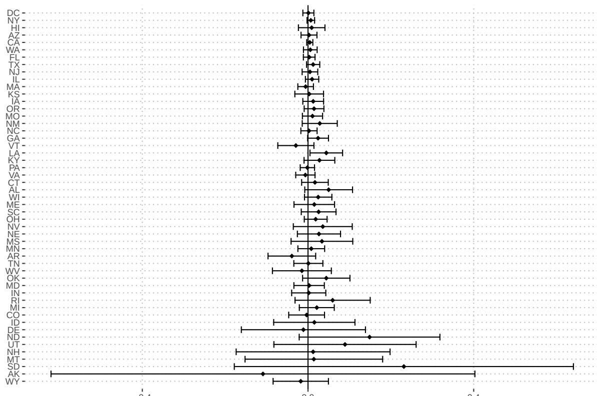
$$Y_{ist} = \rho_s CumulativeChangeFootTraffic_{st} + \alpha^{post}\mathbf{1}(FilingMonth_i = June) + \gamma After_{it} + \varepsilon_{ist} \tag{S.1}$$

where s indexes state, and both Y_{ist} and differences in foot traffic (alternatively, cumulative per-capita case counts) are transformed using an inverse hyperbolic sine function. The idea is that ρ_s captures the effect of diminished foot traffic (or COVID-19 cases) on charities that filed in state s, where the magnitude of the coefficient might be expected to vary depending on the severity of the pandemic in a given state. These estimates will be biased towards zero if the charities in our sample operate in more than one state. Furthermore, Callaway, Goodman-Bacon, and Sant'Anna, (2021) argue that ρ_s might identify both the causal effect of additional exposure to COVID-19 and selection into filing month.

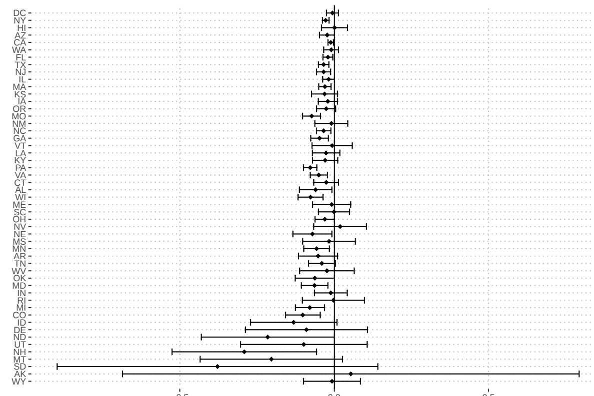
S.0.3 Results

Estimates of the coefficient ρ_s from Equation (S.1) are presented in Figure S.1. For the most part, COVID-related changes in foot traffic did not affect charity outcomes. Alternative figures were produced using COVID per-capita case counts, and are qualitatively similar to those presented here. These alternative results are available upon request.

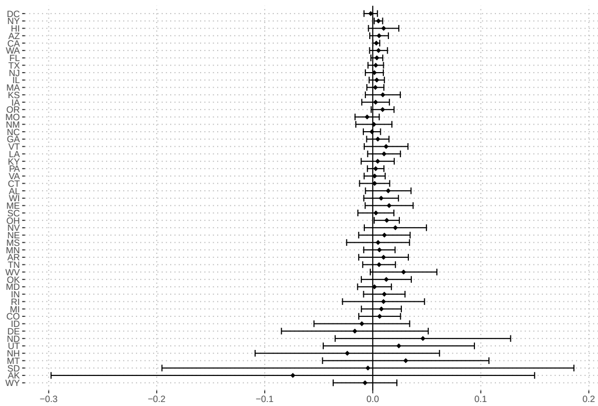
[5]Organizations ending the filing year in months other than June, December, January, or February are omitted from these specifications.



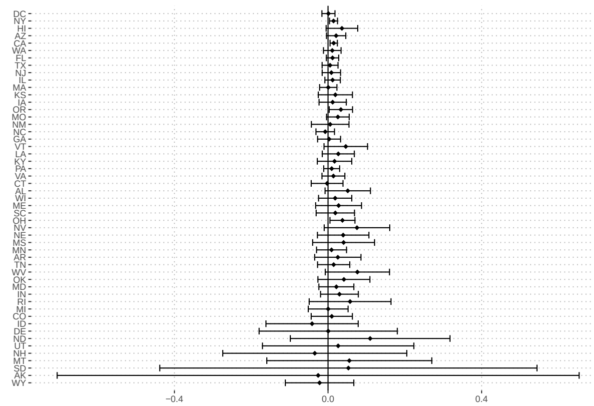
(a) Private Contributions



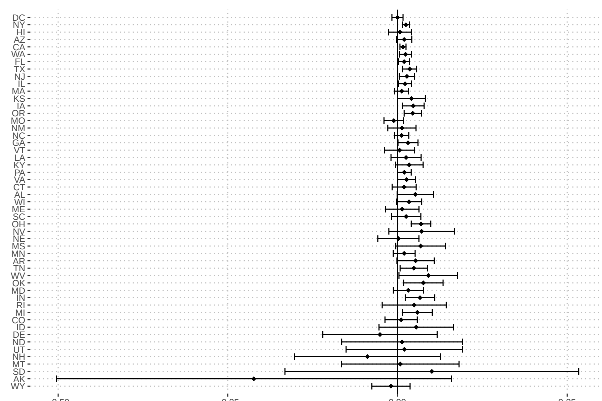
(b) Government Grants



(c) Employees



(d) Salaries



(e) Program Service Expenses

Notes: Figures depict 95% confidence intervals. Standard errors are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. All dollar figures in thousands of constant 2015 dollars.

Figure S.1: Average Treatment Effect of Dose $CumulativeChangeFootTraffic_{st}$

APPENDIX T

Appendix Tables

Table T.1: Difference-in-difference With Controls

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
Any Exposure · After	-0.140***	0.734***	-0.082***	-0.268***	-0.258***
	(0.036)	(0.064)	(0.012)	(0.031)	(0.022)
Any Exposure	-0.300***	1.574***	0.517***	1.248***	0.682***
	(0.059)	(0.179)	(0.035)	(0.100)	(0.028)
After	0.117***	-0.111*	0.023**	0.160***	0.141***
	(0.021)	(0.060)	(0.009)	(0.030)	(0.018)
Observations	340565	340565	340565	340565	340565
R^2	0.058	0.092	0.213	0.138	0.259

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
Dependent variables are transformed via inverse hyperbolic sine function.
All specifications control for state population, charity assets, as well as sector and time fixed effects.

Table T.2: June Filers With Asset Levels Below the 25th Percentile

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
June Filers · After	-0.189***	0.356***	-0.033*	-0.170**	-0.296***
	(0.053)	(0.079)	(0.019)	(0.071)	(0.043)
June Filers	-0.057	1.836***	0.446***	1.456***	0.795***
	(0.080)	(0.171)	(0.043)	(0.203)	(0.067)
After	0.185***	0.001	0.041***	0.227***	0.166***
	(0.033)	(0.034)	(0.010)	(0.036)	(0.036)
Constant	9.722***	1.853***	0.985***	6.286***	11.456***
	(0.080)	(0.112)	(0.037)	(0.153)	(0.067)
Observations	75267	75267	75267	75267	75267
R^2	0.001	0.034	0.017	0.009	0.008

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
Dependent variables are transformed via inverse hyperbolic sine function.
Sample restricted to organizations with assets less than $185,344 in FY2018.

Table T.3: June Filers With Asset Levels Above the 75th Percentile

	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
June Filers · After	0.133*	1.252***	-0.053	-0.142*	-0.259***
	(0.068)	(0.130)	(0.042)	(0.074)	(0.035)
June Filers	0.302*	1.954***	0.746***	1.091***	0.918***
	(0.168)	(0.222)	(0.069)	(0.129)	(0.051)
After	-0.138**	-0.188**	0.017	0.085	0.183***
	(0.057)	(0.079)	(0.035)	(0.064)	(0.028)
Constant	11.505***	4.626***	3.459***	12.160***	15.025***
	(0.138)	(0.191)	(0.054)	(0.108)	(0.047)
Observations	70069	70069	70069	70069	70069
R^2	0.001	0.035	0.017	0.007	0.020

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
Dependent variables are transformed via inverse hyperbolic sine function.
Sample restricted to organizations with assets greater than $3,076,009 in FY2018.

Table T.4: Extensive-Margin Results

	(1) Program Services	(2) Private Contrib.	(3) Gov. Grants
Any Exposure · After	-0.003**	-0.003	0.054***
	(0.001)	(0.003)	(0.005)
Any Exposure	0.020***	-0.018***	0.132***
	(0.002)	(0.004)	(0.013)
After	0.003***	0.005**	-0.007*
	(0.001)	(0.002)	(0.004)
Constant	0.960***	0.834***	0.248***
	(0.003)	(0.005)	(0.015)
Observations	341758	341758	341758
R^2	0.003	0.001	0.030

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
A linear probability model is used, where dependent variables are indicators denoting positive values.

Table T.5: Intensive-Margin Results

	(1) Program Services	(2) Private Contrib.	(3) Gov. Grants
Any Exposure · After	-0.321***	-0.202***	-0.132***
	(0.023)	(0.025)	(0.028)
Any Exposure	1.103***	0.317***	1.016***
	(0.034)	(0.041)	(0.079)
After	0.189***	0.162***	0.095***
	(0.022)	(0.024)	(0.020)
Constant	12.497***	11.668***	11.734***
	(0.030)	(0.042)	(0.066)
Observations	331938	282732	109960
R^2	0.055	0.003	0.044

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
Dependent variables are log-transformed.

Table T.6: Effect on Civil Rights Organizations vs. Other Charities

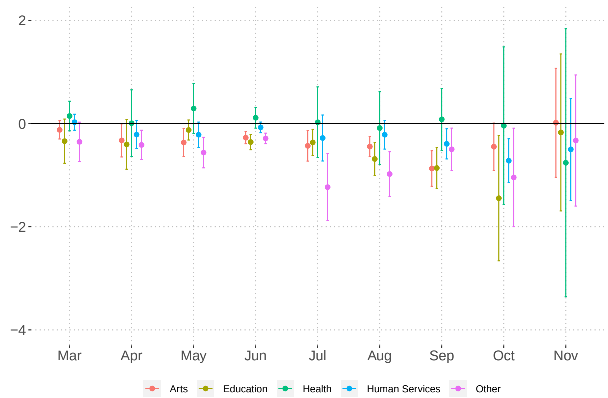
	(1) Private Contrib.	(2) Gov. Grants	(3) Employees	(4) Salaries	(5) Program Services
	Panel A: Non-Civil Rights Organizations				
β^{post}	-0.200***	0.686***	-0.138***	-0.405***	-0.344***
	(0.036)	(0.068)	(0.017)	(0.041)	(0.027)
Observations	339379	339379	339379	339379	339379
R^2	0.000	0.036	0.040	0.023	0.037
	Panel B: Civil Rights Organizations				
β^{post}	-0.166	0.633**	0.002	-0.159	-0.309***
	(0.207)	(0.261)	(0.097)	(0.276)	(0.104)
Observations	2379	2379	2379	2379	2379
R^2	0.005	0.099	0.055	0.051	0.028
	Panel C: Difference in Treatment Effects				
F	0.029	0.031	2.161	0.760	0.099
$p>F$	0.865	0.861	0.148	0.388	0.754

Notes. *p<0.1; **p<0.05; ***p<0.01.
Standard errors in parentheses are clustered at the state-level.
Dependent variables are transformed via inverse hyperbolic sine function.
All specifications control for sector and time fixed effects.
β_1 refers to the coefficient on Any Exposure $\cdot$ After, as in Specification (3.1).

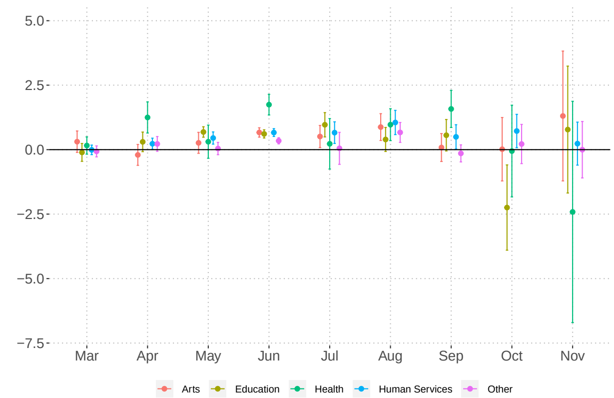
APPENDIX U

Effect of COVID-19 Exposure by Sector and Filing Month

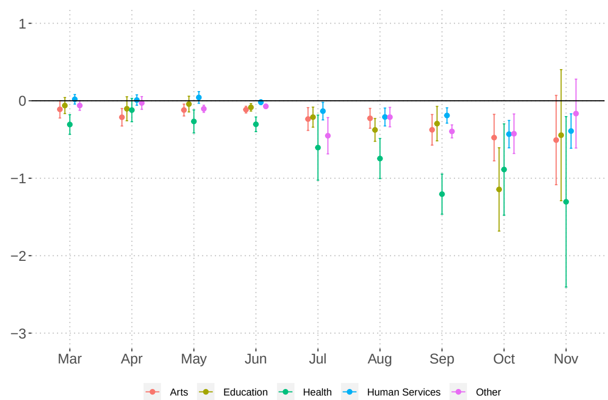
If nonprofit sectors are not evenly represented across filing months, the estimates presented in Figure 3.3 may mask heterogeneity by sector. The below figures break out the estimates of Equation (3.2) by major NTEE group.



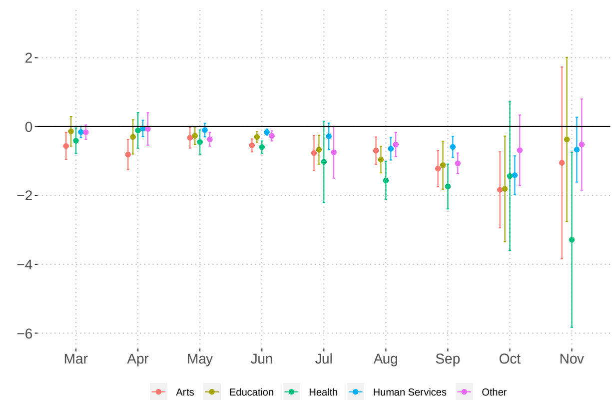
(a) Private Contributions



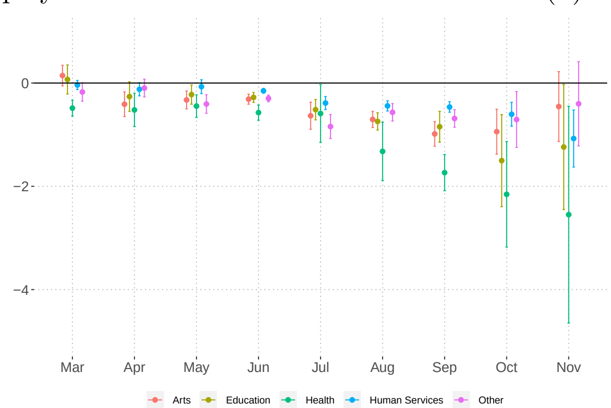
(b) Government Grants



(c) Employees



(d) Salaries



(e) Program Service Expenses

Notes: Figures depict 95% confidence intervals. Standard errors are clustered at the state-level. Dependent variables are transformed via inverse hyperbolic sine function. All dollar figures in thousands of constant 2015 dollars.

Figure U.1: Average Treatment Effect of Dose $m - 2$, by Sector

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