Three Essays in Humanitarian Operations Management

by

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ABSTRACT

Nonprofits and humanitarian organizations play a critical role in the modern world. Yet, to operate sustainably, they often encounter challenges including financial insecurity and operational obstacles. My dissertation investigates nonprofits' decisions and strategies for delivering sustainable services from the perspectives of financial security and operations in short- and long-term horizons.

The first chapter is focused on the role of governance quality in nonprofits' donation income. Donors, generally, support charities that maintain higher program spending ratios (PSR). Yet, PSR does not reflect charities' actual social impact, and a focus on PSR may eventually limit their capacity in providing humanitarian aid. Since 2008, as a result of a policy change by the U.S. Internal Revenue Service, nonprofits are able to better display their governance quality. My empirical investigation shows that governance quality is now an important factor in driving donations to nonprofits, although PSR still remains a key driver. Results suggest that nonprofits should consider improving their governance quality in their strategies for securing donation income, although that may lead to lower PSRs.

Pressures resulted from the focus on PSR encourage nonprofits to prioritize strategies that enable them to report higher program expenses. In the second chapter, I empirically examine one of these strategies, grant provision, that allows nonprofits to increase their reported program expenses without having to spend their funds on their own programs. I find that providing grants to other organizations enables nonprofits to earn more revenue and make a bigger social impact in the long term, but this strategy increases the administrative burden needed to make an impact.

Given the challenges in coordination and lack of effective coordinated response in humanitarian operations, in the third chapter, I develop a non-cooperative game theoretical model to analyze horizontal coordination among non-governmental organizations in disaster relief operations in centralized and decentralized models. I show that coordination does not always maximize social welfare, and time inefficiencies due to bureaucracies involved in coordination mechanisms are substantial obstacles against higher levels of coordination, especially in urgent response operations. I also show that decentralization of coordination mechanisms increases both coordination levels and social welfare.

DEDICATION

To Sara

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Chapter 1

DOES GOVERNANCE EASE THE OVERHEAD SQUEEZE EXPERIENCED BY NONPROFITS?

Abstract

Nonprofits' performance is often evaluated based, in part, on their *program spending ratio* (PSR). Yet, ranking nonprofits based on PSR has been criticized because it is an imprecise index of a nonprofit's actual social impact. Further, too much emphasis on PSR creates an incentive for nonprofits to increase their program spending at the expense of investing in overhead, regardless of the social value it generates. In extreme cases, excessive focus on PSR can create incentives to manipulate or even misreport financial statements. Communicating information regarding governance can potentially counterbalance the pressures created by this focus on PSR. In 2008, the U.S. Internal Revenue Service (IRS) implemented significant changes in the type of information that nonprofits are required to disclose, which helps them to better display their governance quality. Studying the tax forms of 38,226 nonprofits active in social services and relief operations during 2010–2017, we find that governance quality is now an important factor in driving public donations to nonprofits, though PSR still remains a key driver. Moreover, our findings show that better governance is associated with lower likelihood of misreporting, consistent with the argument that better governance reduces the pressure to report a high PSR. Overall, our results suggest that nonprofits should consider improving their governance quality in their strategies for securing donation income, even though that may lead to lower PSR levels.

1.1 Introduction

Nonprofits and social services organizations play a critical role in solving social issues in the modern world. As resource dependent organizations, their operations rely significantly on donations. In 2020, Americans donated over USD 470 billion (Giving USA, 2021) to more than 1.71 million tax-exempt nonprofit organizations registered with the Internal Revenue Service (IRS, 2022). Most charitable giving comes from individuals (e.g., 69% in 2020), followed by foundations and corporations (Giving USA, 2021). The growth of the nonprofit sector is considered beneficial for society but increases competition among nonprofits (Castaneda *et al.*, 2008; Berenguer and Shen, 2020). This challenge is further magnified during an economic decline when demand for social services surges. For example, during the 2008 economic recession, nonprofits' donation income rapidly declined with a 6% decrease in individual giving (Shin, 2020), while demand for charitable activities sharply increased (Calabrese, 2013). Therefore, despite their value, nonprofits often encounter financial turbulence and high risk of failure, and so securing donations is an important goal in their strategies (Calabrese, 2013).

Traditionally, donations are linked to *program spending ratio* (PSR), the ratio between the nonprofit's expenses on core programs and its total expenses (Gneezy *et al.*, 2014). Put differently, a nonprofit's PSR informs donors of the portion of their donations that is spent directly on the nonprofit's core missions. Recent studies show increasing trends in nonprofits' PSR levels in the US (Lecy and Searing, 2015) and in Germany (Schubert and Boenigk, 2019). Industry practitioners, however, believe that too much emphasis on PSR fuels a "starvation cycle" where donors are *trained* to expect unrealistically low overhead costs, and so nonprofits either continuously increase their PSR (and leave little or nothing for management or reserves), or misreport high PSRs to stay competitive in charitable markets (Gregory and Howard, 2009).

On the other hand, given that donors are sensitive to issues such as a nonprofit's mismanagement of resources, managerial expertise, and budget allocation policy (Ebrahim, 2009; Zhuang *et al.*, 2014), the nonprofit's transparency and accountability should also be key to earn donors' trust (Devalkar *et al.*, 2017; Becker, 2018). Stated differently, it is likely that donors react to "how" their donation is spent, instead of only being concerned about "how much" of their donation is spent on programs. Accordingly, the conventional wisdom indicates that disclosure of financial, management quality, and programs-related data is a solution to information asymmetry that should increase donors' trust (Saxton and Guo, 2011; Zhuang *et al.*, 2014). Despite the importance of accountability and transparency in the nonprofit sector, there is little in the academic literature that studies their role in counterbalancing the pernicious effects of the excessive focus on PSR. The goal of this paper is to address this gap.

1.1.1 Program Spending Ratio

Studies show that donors support nonprofits with higher PSR (Gneezy *et al.*, 2014; Yan and Sloan, 2016). For example, in a recent experimental study, Exley (2020) shows that donors use low PSR as an excuse not to give. Using PSR as the main criterion to rate nonprofits' performance has been reinforced by watchdog organizations that apply financial ratios to gauge nonprofits' performance: The Better Business Bureau Wise Giving Alliance explicitly warns against donating to nonprofits whose PSR is below 65% (Taylor, 2007), and Charity Navigator recognizes efficient nonprofits as those with a PSR of at least 75% (Exley, 2020). The attraction of PSR has been attributed to donors' perception that if their donation is directly spent on a nonprofit's core programs, they "personally made a difference" (Duncan, 2004). Accordingly, in the absence of other information, donors infer organizational performance from PSR and associate low PSRs with inefficiency or even malpractice or corruption (Kinsbergen and Tolsma, 2013; Gneezy *et al.*, 2014).

On the other hand, the focus on PSR has been criticized for a number of reasons. First, it neither reflects a nonprofit's actual performance, nor the real social value of its missions (Glassman and Spahn, 2012; Eftekhar *et al.*, 2017; Coupet and Berrett, 2019). Second, achieving higher PSR motivates organizations to spend more over the current fiscal year, and so intensifies a myopic spending pattern. Nonprofits maintain little or no operating reserves lest they lose public donations. For example, a field study demonstrated that nearly 60% of nonprofits based in Washington D.C. had reserves of fewer than three months of expenses, and about 30% had no operating reserves at all (Blackwood and Pollak, 2009). Therefore, overemphasizing PSR and cutting overheads provide counter-productive incentives in the long term; It can inhibit program outcomes (Altamimi and Liu, 2019) and sustainability of nonprofits (Park and Matkin, 2021), and impedes their ability to respond to fluctuating economic conditions (Mitchell, 2017). Third, reports of high PSR may not be reliable due to misreporting financials, if a nonprofit organization tries to make itself look more attractive by artificially inflating its PSR (Garven *et al.*, 2016).

1.1.2 Governance Quality

It is assumed that donors' concerns regarding the use of their donations can be alleviated by implementing better governance practices (Newton, 2015). In 2008, in an attempt to increase transparency, the U.S. Internal Revenue Service (IRS) implemented significant changes in the type of information that nonprofits were required to disclose. This change requires nonprofits to provide additional information regarding governance and accountability (Newton, 2015) making it easier for donors to compare nonprofits' governance quality while making donation decisions. Following this IRS policy change, Charity Navigator introduced "transparency and accountability" as a new dimension to its rating methodology which mainly relies on this newly available information (Charity Navigator, 2016). The additional information addresses donors' major concerns regarding a nonprofit's overheads. For instance, it includes whether nonprofits' financial statements are audited, what policies the nonprofit follows to determine CEO compensation, whether grants were given to officers or directors, and whether the nonprofit had business relationships with directors, employees, or related individuals. Therefore, the IRS policy that requires nonprofits to be more transparent provides them with an opportunity to better communicate their governance quality.

Better governance practices, such as independent audits and oversight committees, increase the reliability of the reported financials and decrease the potential for misreporting (Ebrahim, 2009; Newton, 2015; Garven *et al.*, 2018). For example, if financial statements are compiled by an independent accountant and tax forms are presented to a governing body consisting mostly of independent members, the reported numbers, such as PSR, are more reliable than if these conditions are not met. In other words, while donors may associate low PSRs with inefficiency or malpractice or even corruption (Kinsbergen and Tolsma, 2013; Gneezy *et al.*, 2014), governance quality may offer a more reliable signal regarding the potential for corruption. For instance, nonprofits exhibit lower quality if they report that grants were paid to their directors, or that CEO compensation was not determined through a process with approval of a governing body to ensure comparability with similar nonprofits.

1.1.3 An Operations Management Perspective

A fundamental difference between the operations in nonprofit organizations and commercial firms lies in their financial structure. Charities' most pressing challenge is to encourage donations which is further magnified during times of economic decline (Osili *et al.*, 2019). Studies show how budget uncertainty and earmarked and inflexible budgets lead to limited ability to serve the target populations and an overall lower performance of relief systems that eventually increases human suffering (Keshvari Fard *et al.*, 2019; Eftekhar *et al.*, 2022). Accordingly, donation income is the critical resource for nonprofits, and it influences viability, sustainability, efficiency, and scalability of nonprofit operations (Lewis, 2004; Berenguer and Shen, 2020). Funding concerns contribute to nonprofits' challenges in recruiting quality staff (Wolf, 1999), coordination (Eftekhar *et al.*, 2017), investments in information technology, data collection, and demand forecasting (Berenguer and Shen, 2020), and force them to make myopic decisions (Arya and Mittendorf, 2016; Keshvari Fard *et al.*, 2019).

Budget allocation (i.e., the level of spending on programs, fundraising, and administration) is a critical challenge for nonprofits, because the reaction of donors to these expenditures is largely unknown. Nonprofits have to spend on fundraising (in order to collect donations), should spend on management and administration (to hire quality staff and operate effectively), and should build up a reasonable level of reserves (to cope with financial shocks), which are all typically thankless actions. For example, an executive of a large international humanitarian organization, mainly involved in distributing foods and medicines in poor countries, said to us: *"We do not have supply chain experts in the headquarters; in order to keep the overheads low [...] all supply chain tasks are done by our accounting team."* This is an obvious example of how the focus on PSR affects the actual performance of even major humanitarian organizations. Nevertheless, if nonprofits can secure donations by emphasizing other attributes, such as their governance quality, they may be better able to tackle this challenge. While the OM literature offers insights on how to optimally allocate budgets in distribution and in last mile delivery in humanitarian settings (Vanajakumari *et al.*, 2016; Eftekhar *et al.*, 2022), this paper highlights the role of budget allocation decisions on nonprofits' capacity and income.

Donors also have a role in monitoring nonprofit operations, although based on inaccurate measures (Berenguer and Shen, 2020). In that regard, information disclosure regarding governance practices allows donors to better monitor nonprofits. Potential managerial misconduct and use of nonprofit funds for purposes other than the organizations' missions are among the governance issues that have adverse impacts on their operations (Molk and Sokol, 2021). Further, better governance is associated with higher efficiency in operations (Newton, 2015). For instance, nonprofit governing model and board composition can significantly influence organizational and operational efficiency (Callen *et al.*, 2003). The literature has investigated the relationship between governance mechanisms and governance quality and factors such as organizational performance and CEO compensation, in both for-profit and nonprofit settings (Cyert *et al.*, 2002; Newton, 2015). This paper, however, aims to highlight the role of governance in enabling nonprofits to avoid challenges resulting from the emphasis on PSR. Because enhancing governance quality can be used to communicate the quality of services that a social services organization offers, it reduces the pressure to increase PSR to secure donations, and so the organization has more flexibility in terms of how to allocate its budget to different functions.

1.1.4 Contribution of This Paper

In this paper, we re-examine whether the role of PSR as a determinant of nonprofits' donation income has persisted in recent years, after the IRS policy change. Next, we examine whether governance quality is also a means for nonprofits to secure more donations. To measure governance quality, we use a comprehensive index developed by Newton (2015) that evaluates multiple governance mechanisms of nonprofits. It is made up of four categories (governing body, governing policies, compensation policies, and accountability) that together contain sixteen components derived from the new sections of the redesigned version of IRS Form 990.

We focus on public donations because the majority of charitable giving comes from individuals, e.g., 69% in 2020 (Giving USA, 2021). Further, nonprofits receive government grants through formal applications and proposals, for which specific requirements need to be met (Andreoni and Payne, 2003). In some cases, government grants are more similar to contracts than granted funds in their common definition, and the recipient nonprofits' performance is likely to be more closely inspected than is possible based solely on publicly available information (Andreoni and Payne, 2003; Devalkar *et al.*, 2017). On the other hand, a survey shows that less than 32% of individuals might spend any time investigating the performance of nonprofits before making a donation (Hope Consulting, 2010). Researchers attribute this to the cost and difficulty for ordinary citizens to find financial information of nonprofits (Balsam and Harris, 2014). Focusing on public donations allows us to better capture the impact of PSR and governance on donations through public information sharing channels.

Our dataset contains information of 38,226 US-based nonprofits in "social services and relief" during 2010–2017 that filed IRS Form 990, which is the primary source of public information on nonprofits (Harris *et al.*, 2015). The focus on social services and relief nonprofits is motivated by the importance of their contribution in the charitable market. In 2020, Americans donated more than USD 65 billion to these organizations, which constitutes 14% of all contributions to nonprofits (Giving USA, 2021). Moreover, securing donations is extremely critical for this sector because these nonprofits are limited in alternative sources of income that further distinguishes them from other nonprofits such as museums, healthcare centers, or educational institutions that generate a considerable portion of their revenue from their core programs.

To address potential omitted variable bias, we investigate the within-organization effects of PSR and governance on nonprofit organizations donation income. While confirming that PSR still remains an important driver of donations, our results show that governance also plays a significant role in driving donations and hence can counteract the emphasis on PSR. Other work has shown that reporting zero fundraising expenses is an indicator of potential misreporting (Krishnan *et al.*, 2006). We find that better governance is associated with lower likelihood of reporting zero fundraising expenses, pointing to at least one mechanism through which governance reduces the pressure to report artificially high PSR. Overall, we find that as an average nonprofit exhibits better governance, it is able to earn more donations, despite it being associated with lower PSR levels. Therefore, nonprofits should consider developing governance quality and accountability while designing their strategic plan.

At a high level, the present paper shows that there are practical policies to avoid the starvation cycle. Although most of the existing studies show that nonprofits are forced to keep their PSR high, they do not provide a solution to alleviate the excessive impact of PSR on public donations. Gneezy *et al.* (2014) is among the very few studies that provides a solution; while demonstrating the impact of overhead costs on donations in a lab-experimental setting, the authors show the role of donors' preference for a direct impact on a charitable cause over an impact through overheads. Consequently, they suggest an "overhead-free solution" where organizations initially raise seed money to cover the overheads. Nevertheless, not all nonprofits are able to implement such a solution. Results of this study demonstrate that providing additional information about how resource use is governed, other than financial ratios, can be a solution that allows nonprofits with lower PSRs to secure donations. In that regard, we note that the increased transparency that led to disclosure of governance quality information was the result of a sector-wide policy, highlighting the role of policy makers in helping nonprofits to avoid the starvation cycle.

Further, the existing evidence on the role of PSR is typically based on experimental studies (Bekkers and Wiepking, 2011). Although these methods have many advantages (e.g., a potential to show causal inferences), they reflect a short-term effect of manipulations, and rely on small groups of participants who may or may not be the actual donors. This study empirically illustrates actual donors' aggregate reaction over a long-term horizon.

Finally, while recent studies experimentally examine the roles of multiple factors, including donors' self-serving biases (Exley, 2020), subjective preferences (Berman *et al.*, 2018), commitment to the cause (Newman *et al.*, 2019), and social image (Butera and Horn, 2020) on donors' attitude towards PSR, the impact of governance and accountability and their relationship with PSR and donations have largely been overlooked (Dang and Owens, 2020). This paper aims to address this gap, noting that governance practices can play an important role in solving problems that arise in the nonprofit sector which are mainly due to lack of incentives and disciplining devices (Bolton and Mehran, 2006). Manipulations in reported ratios can generally remain undetected by donors which creates incentives for misreporting (Garven *et al.*, 2016). For instance, while Krishnan *et al.* (2006) find that reporting zero fundraising expenses is at least partially due to misreporting, Jacobs and Marudas (2012) show that donors do not find reports of zero fundraising expenses to be less reliable. In a theoretical study, Privett and Erhun (2011) propose using audit contracts between funders and nonprofits to tackle unreliability of self-reported metrics. However, the literature shows that various governance practices such as regular financial audits and oversight by monitoring institutions also increase the accuracy of reported financial information and reduce the likelihood of misreports (Parsons *et al.*, 2017).

This paper makes the following contributions: First, earlier work has shown that governance quality can help enhance a nonprofits' reputation among donors; we find a positive association between governance quality and higher public donations. Second, researchers have documented an overemphasis on PSR and the consequences of this focus; we provide empirical evidence that disclosure of governance information is associated with lower pressure to increase PSRs. Third, research has shown that average PSRs were increasing over time during earlier time periods; we find that during 2010-2017 that is no longer the case. Fourth, earlier work has suggested that reporting zero fundraising is an indicator of potential misreporting; we document a strong association between better governance and lower likelihood of reporting zero fundraising.

1.2 Research Setting and Data

The dataset for this study includes information of U.S. based nonprofits that operated during 2010–2017. We use organizations' digitally filed Forms 990 that are publicly available and provide general information about each organization, including their missions, board members, number of employees, number, type, and expenses of main programs, as well as financial data such as revenue (i.e., public donations, government grants, and own income that includes program and service revenue as well as investment and other income), expenses (including programs, fundraising, administration), assets, and liabilities. These forms also contain information about organizations' governance, accountability, and transparency, and include information such as board composition and independence, audits, methods of sharing information with the public, and compensation, conflict of interest, and whistleblower policies.

We created our dataset in two steps. First, we collected the list of social services and relief organizations from the latest National Center for Charitable Statistics (NCCS) Core File, which includes all the public charities that were required to file IRS Form 990 or Form 990-EZ in 2017. To filter social services and relief organizations, we used their National Taxonomy of Exempt Entities (NTEE) Codes, and similar to Andreoni and Payne (2003), we included organizations with NTEE classifications C, I, J, K, L, P, and S, as social service organizations, excluding organizations with codes less than 19 (i.e., professional societies, management and technical assistance, research institutes, and specific fundraising organizations) and those classified as P86 and P87 (i.e., institutes for the blind and the deaf or hearing impaired). Examples of included organizations provide services to human trafficking survivors, provide community development services to marginalized groups, help people with disabilities, and advocate for human rights and women's rights. We also selected relief organizations with NTEE classifications M that include public safety, disaster preparedness and relief, and Q33 that represents international relief. In sum, we collected the data of a total of 122,006 organizations. Next, we used the database of digitally filed Forms 990 that the IRS has made public on Amazon Web Services and collected all the available forms for these organizations. This resulted in 330,627 organization-year observations of 58,994 organizations over the years 2009–2017. Note that these data exclude smaller organizations that only reported Form 990-EZ, a shorter version of Form 990 that does not include governance quality information. Also, due to the number of missing values in the data for 2009, we limit our analysis to the years 2010–2017. Similar to the literature (Andreoni and Payne, 2011), we excluded organizations with zero public donations reported in all years of observation, organizations with less than 3 years of data, observations with non-positive total expenses, non-positive assets, negative program expenses, program expenses more than total expenses, negative fundraising expenses, non-positive revenue, negative public donations, and negative government grants. We also removed very large organizations, categorized as Economic Engine nonprofits by GuideStar, with average total expenses greater than USD 50 million. These represented only about 1% of our original data. In addition, we removed observations in the bottom one percentile of own income, which includes reports of very large losses, and observations with negative reported earmarked assets. Our final dataset is comprised of 220,971 organization-year observations of 38,143 organizations. The average nonprofit in our data has USD 5.19M in assets, receives about USD 682K public donations, and spends about 55K USD on fundraising investments.

1.3 Methods

To examine the role of PSR and governance in driving donations, we consider Equation (1.1),

$$\begin{aligned}\log(Donations_{it}) =& \alpha_1 PSR_{i(t-1)} + \alpha_2 Governance_{i(t-1)} + \alpha_3 \log(Assets_{i(t-1)}) \\ &+ \alpha_4 \log(GovernmentGrants_{i(t-1)}) + \alpha_5 \log(OwnIncome_{i(t-1)}) \\ &+ \alpha_6 \log(Earmarked_{i(t-1)}) + \alpha_7 ProgramConcentration_{i(t-1)} \\ &+ \alpha_8 \log(Fundraising_{it}) + \phi_t + v_i + u_{it}, \qquad (1.1)\end{aligned}$$

where the dependent variable is the natural logarithm of *annual public donations* representing contributions from individual citizens, foundations, and corporations.

Given the wide range of nonprofits' size in our data, we use log-transformed values for donations. This transformation, aligned with previous studies (Mendoza-Abarca and Gras, 2019), mitigates skewness and heterosedasticity in the residuals. We have two explanatory variables. We measure *PSR* as the percentage of total costs spent on all programs and services (Exley, 2020), and we measure *governance* using the index developed by Newton (2015). This index evaluates multiple governing mechanisms of nonprofits. It contains sixteen components derived from the new sections of the redesigned version of Form 990, most of which are yes-no questions coded as indicator variables, categorized in four sub-indices; governing body, governing policies, compensation policies, and accountability. For each organization-year observation, each sub-index score is calculated as the ratio between the sum of the component scores of that observation and the total possible score in that sub-index. For instance, an organization that makes its tax forms available on its website and has its financial statements audited by an independent accountant with the oversight of an audit committee receives all the 3 possible points in the accountability sub-index, i.e., a score of 100. If there was no oversight committee, all else equal, the organization would have a score of 67 in this sub-index. Governance is then calculated as the average score of the nonprofit in that year in these four sub-indices, and ranges between zero and 100. For example, if an organization receives 80%, 80%, 60%, and 60% of the possible scores in the four sub-indices in a given year, its governance score equals 70. (See Appendix A for details.)

Given that information about nonprofits' operations is generally disclosed with a 1-year delay, we consider a 1-year time lag for our explanatory variables, as well as our control variables: First, as an organization's size is a commonly used variable in similar studies, we control for its effect by considering the natural logarithm of organizations' total *assets* in each year (Kinsbergen and Tolsma, 2013). Second, we control for the effect of *government grants* as its crowding out/in effect has been widely studied in public economics (Andreoni *et al.*, 2014). Donors are also taxpayers who may consider government grants as part of their own contribution to nonprofits, i.e., a crowd out effect (Andreoni and Payne, 2003). Simultaneously, they might consider government grants as an indicator of the organizations' capabilities or capacity, i.e., a crowd in effect (Andreoni and Payne, 2011). Third, a nonprofit's financial capacity, including revenue from services and investments, ensures the continuity of their operations and so it affects public donations (Yan and Sloan, 2016). Consequently, we consider the natural logarithm of organizations' *own income* as a control variable assuming that when a nonprofit has higher own income, it might be able to assure donors that their donation is spent directly on the programs because the organization's other income covers the overheads (Gneezy *et al.*, 2014). Fourth, the set of programs that an organization provides influences donations. Because donors differ in the type of charitable programs they prefer to support (Rose-Ackerman, 1982; Andreoni and Payne, 2003), it is reasonable to expect that a wider range of programs increases donations. On the contrary, donors might prefer that the nonprofit specializes in a limited range of services (Bilodeau and Slivinski, 1997; Penna, 2011). We therefore control for nonprofits' *program concentration* measured by the Herfindahl-Hirschman index (HHI) of the organizations' expenses on their main programs reported on Form 990. Note that a lower HHI indicates higher diversification and higher HHI indicates higher concentration (an HHI equal to 1 shows perfect concentration). Further, donors prefer to have higher control over their contributions. Hence, earmarking is associated with higher donation income (Nunnenkamp and Ohler, 2012). We therefore control for the natural logarithm of nonprofits' *earmarked assets*, calculated as the summation of temporarily and permanently restricted net assets reported in Form 990 in the given year. Also, given that nonprofits' fundraising efforts drive significant donations, we control for the natural logarithm of *fundraising investment*. Finally, our data contain multiple measures per subject, which are repeated at each period and thus might cause correlated errors. We therefore account for all observed and unobserved time-invariant differences between organizations by including organization fixed effects. We also include year dummies in our model to account for year-fixed effects.

A key premise of our work is that nonprofits may choose to invest in better governance to reduce reliance on PSR. In other words, a nonprofit may view its ability to exhibit a high level of governance quality as an opportunity to retreat from cutting overheads. Further, the observed PSR values are based on the expenses that organizations report, and so they could be the result of PSR management and misreporting (i.e., nonprofits' attempts to appear more efficient). However, as organizations enhance their governance quality, they are presumably less likely to engage in such practices. Better governance practices, such as audits, decrease potential for misreporting and result in more realistic reported financials (Yetman and Yetman, 2011; Garven *et al.*, 2018). Thus, higher governance can lead to lower reported PSRs. Also, some of these efforts to increase governance can incur costs, including time investments by staff or board members. For instance, independent audit costs can exceed USD 20,000 for large organizations (National Council of Nonprofits, 2021). (In our data, this value is equivalent to an average 1% increase in administrative expenses of large nonprofits.) Because some nonprofits might deliberately invest in better governance to make a lower PSR acceptable to donors, this potential relationship between governance and PSR must be addressed. We capture this relationship by Equation (1.2).

$$
\begin{aligned}
PSR_{i(t-1)} =& \beta_1 Governance_{i(t-1)} + \beta_2 \log(Assets_{i(t-1)}) \\
&+ \beta_3 \log(GovernmentGrants_{i(t-1)}) + \beta_4 \log(OwnIncome_{i(t-1)}) \\
&+ \beta_5 \log(Earmarked_{i(t-1)}) + \beta_6 ProgramConcentration_{i(t-1)} \\
&+ \beta_7 ZeroFundraising_{i(t-1)} + \beta_8 LiabilityToAsset_{i(t-1)} \\
&+ \phi_{(t-1)} + \gamma_i + \epsilon_{i(t-1)}. \qquad (1.2)
\end{aligned}
$$

Following the literature, we use two additional control variables in Equation (1.2): we add *liability to asset* ratio that indicates the organization's leverage which creates incentives for misreporting (Newton, 2015), and a dummy variable that indicates whether the organization reported *zero fundraising expenses*, which is an indicator of reporting reliability, in light of the tendency of some nonprofits to incorrectly report fundraising costs as program expenses (Krishnan *et al.*, 2006; Harris *et al.*, 2015; Newton, 2015). Tables 2.1 and 2.2 provide descriptive statistics and correlations of the variables used in the estimations, respectively. Appendix B provides summary statistics of raw values before log-transforming.

1.3.1 Mixed-effect Estimation: Initial Results

The panel structure of our data provides the possibility to investigate the effects of interest at two levels: We can study both within-organization effects (i.e., whether changes in PSR and governance levels of a nonprofit lead to changes in its donation income), and between-organization effects (i.e., whether differences in PSR and governance levels across different nonprofits lead to different levels of donation income). Accordingly, in the first step, we should examine the relative influence of within- and between-nonprofit variances of our main variables. We do so by using *intra-class correlation coefficients* (ICCs) that show the between-organization variance in

Table 1.1: Summary statistics and descriptions of variables

Variable	Description	Mean	SD	Min	Max
log(*Donations*)	Natural logarithm of donations from individuals, corporations, and foundations	11.108	3.269	0.000	18.699
PSR	Percentage of total costs spent on programs and services	83.230	16.002	0.000	100.000
Governance	Governance quality score	46.931	16.555	6.250	97.222
log(*Assets*)	Natural logaritm of total assets	13.771	1.931	0.693	20.706
log(*GovernmentGrants*)	Natural logarithm of grants received from government entities	6.351	6.432	0.000	18.141
log(*OwnIncome*)	Natural logarithm of income from sources other than donations and grants	12.463	1.860	0.000	18.305
ProgramConcentration	HHI index of the expenses on reported programs	0.813	0.265	0.000	1.000
log(*Earmarked*)	Natural logarithm of total temporarily and permanently restricted assets	5.494	6.172	0.000	19.045
log(*Fundraising*)	Natural logarithm of fundraising expenses	5.054	5.262	0.000	16.351
log(*Liabilities*)	Natural logarithm of total liabilities	14.409	0.784	0.000	20.463
log(*Occupancy*)	Natural logarithm of total occupancy expenses	12.991	0.426	0.000	17.681
LiabilityToAsset	The ratio between total liabilities and total assets	0.524	20.196	-4.060	6808.438
ZeroFundraising	Indicator variable equal to 1 if reported fundraising expenses are zero; 0 otherwise	0.503	0.500	0.000	1.000
GovernanceIV	Average governance quality of nonprofits similar in size, sector, and location	46.953	9.213	26.539	76.968

For log-transformation of each of the variables with non-positive values, a constant was first added to all values to make the minimum value of that variable greater than zero.

Table 1.2: Correlations of variables used in estimation model

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	log(*Donations*)	1.000													
2	*PSR*	-0.047	1.000												
3	*Governance*	0.219	0.011	1.000											
4	log(*Assets*)	0.192	0.037	0.507	1.000										
5	log(*GovernmentGrants*)	-0.120	0.122	0.171	0.160	1.000									
6	log(*OwnIncome*)	0.092	0.086	0.452	0.645	-0.008	1.000								
7	*ProgramConcentration*	-0.229	-0.018	-0.252	-0.213	-0.193	-0.198	1.000							
8	log(*Earmarked*)	0.341	-0.024	0.426	0.451	0.148	0.277	-0.273	1.000						
9	log(*Fundraising*)	0.462	-0.148	0.319	0.219	0.090	0.129	-0.240	0.404	1.000					
10	log(*Liabilities*)	0.073	0.068	0.401	0.666	0.076	0.635	-0.136	0.236	0.065	1.000				
11	log(*Occupancy*)	0.159	0.086	0.410	0.545	0.144	0.621	-0.243	0.262	0.161	0.660	1.000			
12	*LiabilityToAsset*	-0.011	-0.001	-0.001	-0.040	-0.003	-0.001	0.007	-0.011	-0.011	0.011	0.000	1.000		
13	*ZeroFundraising*	-0.413	0.136	-0.248	-0.136	-0.070	-0.061	0.200	-0.334	-0.966	-0.002	-0.087	0.010	1.000	
14	*GovernanceIV*	0.238	0.094	0.554	0.612	0.213	0.672	-0.316	0.387	0.241	0.578	0.639	-0.001	-0.149	1.000

the variables as a percentage of their overall variance (Certo *et al.*, 2017). In our dataset, the ICCs for donations, PSR, and governance equal 0.73, 0.75, and 0.91, respectively, reflecting that a large proportion of the variations (of our variables) lies between organizations. This suggests the use of multilevel methods that capture both within and between effects (Certo *et al.*, 2017). Therefore, following McNeish and Kelley (2019), we begin with estimating mixed-effects within-between specifications of our equations. These initial results, presented in Table C.1 in Appendix C, are not corrected for endogeneity.

1.3.2 Fixed-Effect IV Estimation

A mixed-effect estimation approach cannot explicitly model endogeneity. Estimates may therefore be biased due to existence of omitted variables. In our setting, there are two potential sources of endogeneity. First, in Equation (1.1), we are concerned about endogeneity of *fundraising investment* because unobserved variables might influence both a nonprofit's fundraising investment and their donation income. For example, a large-scale disaster can increase giving and may decrease or increase the need for fundraising (Andreoni and Payne, 2011). Although the direction of this impact is not clear, it can bias our estimates. Second, in Equation (1.2), *governance* might be the source of endogeneity. Unobserved characteristics could cause correlation between governance and PSR. For instance, a change in management or board may lead to simultaneous improvement in PSR and governance, or a new CEO (or management team) with higher compensation (leading to lower PSR) may improve governance.

A common approach to dealing with endogeneity is to use instrumental variable (IV) estimations, but these can perform worse than the within-between estimates that do not account for endogeneity (Busenbark *et al.*, 2022). We therefore use the *impact threshold of a confounding variable* (ITCV) (Frank, 2000) to investigate the degree of omitted variable bias that needs to be present to invalidate causal inferences from the within-between specification. The ITCV calculates the minimum correlations between an omitted variable and the independent and dependent variables that alter the causal inference of a regression coefficient at a certain p-value (Frank, 2000). We then compare the ITCV value for each coefficient against the partial correlations of our control variables with the independent and dependent variables. Busenbark *et al.* (2022) suggest that if we do not find any control variables with correlations that exceed the ITCV value, it is likely unnecessary to use IV methods. However, the ITCV approach is not definitive as it assumes any confounding variable is similarly correlated with the control variables (Larcker and Rusticus, 2010), which is a strong assumption in itself (Wilms *et al.*, 2021).

In our estimates, multiple control variables have partial correlations that are higher than the ITCV values, especially for the coefficient estimates of governance. Specifically, the ITCV value for the within effect of governance on donation income equals 0.040 at $p = 0.10$, which suggests that if the square root of the product of partial correlations of an omitted variable with donation income and governance is higher than 0.040, the statistical inference that this coefficient is different from zero at $p = 0.10$ is biased. There are four control variables for which this condition holds. For instance, fundraising has partial correlations of 0.366 with donations, and 0.139 with governance. The square root of the product of these partial correlations equals 0.226, which is considerably higher than the ITCV value of 0.040. Accordingly, omitted variables likely bias the within-between estimation of our model.

Specifically, we follow Andreoni and Payne (2011) and instrument fundraising expenses by the natural logarithm of *liabilities* and natural logarithm of *occupancy expenses*, which are indicators of financial security of an organization. Andreoni and Payne (2011) support this choice because nonprofits are aware of their finances in real time and are expected to change their fundraising efforts depending on their financial security. Validity of the instruments also requires that they do not influence donations if fundraising is held constant. In that regard, we note that it is difficult for donors to have contemporaneous information about the nonprofits' financial security at the time that they make their donations. Likely, they consider only the general financial health (or stability) of the nonprofit (Andreoni and Payne, 2011). We control for this general character using the organization fixed effects. Further, occupancy expenses can change when organizations expand or shrink their infrastructure and operations (e.g., more office space and higher utilities), which is expected to change their fundraising investments. On the other hand, donors would not be informed of these changes in real time, except through the changes in fundraising efforts. Further, we also treat governance as endogenous and create an IV similar to the IV used by Newton (2015) for nonprofit performance: the average governance quality of all other nonprofits that are similar in size, sector (relief or social services), and location in that year. A nonprofit's governance quality is expected to be correlated with that of similar nonprofits. If other nonprofits, who are likely to be targeting the same donors, have higher governance quality, the organization is compelled to increase its own governance quality. However, a nonprofit's PSR is unlikely to be influenced by governance quality of other organizations. (For details, see Appendix D.)

We emphasize that if a suspected endogenous variable can in fact be treated as exogenous, using IV methods would result in an unnecessary loss of efficiency (Wooldridge, 2010). Therefore, in addition to the theoretical reasoning above and the potential of bias indicated by the ITCV values, in our estimations, we first use a GMM distance test in separate two-stage least squares (2SLS) estimations of the two equations to determine whether we can treat governance and fundraising as exogenous (Baum *et al.*, 2007). If we can reject the null hypothesis that a variable can be treated as exogenous at $p \leq 0.10$, we treat it as endogenous. The GMM distance test result for endogeneity of $\log(Fundraising_{it})$ in Equation (1.1) and that for endogeneity of $Governance_{i(t-1)}$ in Equation (1.2) reject the null hypothesis that these variables can be treated as exogenous (at $p < 0.001$).

Next, we note that using extra instruments can lead to poor finite sample performance of the estimator, and dropping redundant instruments can result in more reliable estimates (Baum *et al.*, 2007). Therefore, we sequentially test for redundancy of the two IVs used for fundraising and use both IVs only if we cannot reject the null hypotheses that one variable is redundant (Hall and Peixe, 2003). As we estimate Equation (1.1), treating $\log(Fundraising_{it})$ and $Governance_{i(t-1)}$ as endogenous, the Lagrange Multiplier (LM) tests for redundancy of $\log(Occupancy_{it})$ reject the null that it is redundant (at $p < 0.001$). However, based on the LM tests for redundancy of $\log(Liabilities_{it})$, we cannot reject the null hypothesis that it is redundant (at $p = 0.30$). Therefore, we only use $\log(Occupancy_{it})$ as the IV for $\log(Fundraising_{it})$.

Moreover, we use the Anderson-Rubin test, Sanderson-Windmeijer multivariate F test, and the Kleibergen-Paap underidentification test to ensure our IVs are valid (Anderson and Rubin, 1949; Kleibergen and Paap, 2006; Sanderson and Windmeijer, 2016). Specifically, when we estimate Equation (1.1) treating $\log(Fundraising_{it})$ and $Governance_{i(t-1)}$ as endogenous, the Sanderson-Windmeijer multivariate F statistic equals 27.97 and 27.66 for these two variables, respectively, and the Kleibergen-Paap rk LM statistic equals $\chi^2(1) = 25.38$, rejecting the null hypothesis of under-identification denoting that the instruments are relevant (all at $p < 0.001$). Further, the Anderson-Rubin test statistic for the first stage estimation equals $\chi^2(2) = 31.22$ ($p < 0.001$), which is robust to weak instruments (Anderson and Rubin, 1949). Similarly, the Kleibergen-Paap rk Wald F statistic equals 12.67 which indicates that weak identification is not a concern (Stock and Yogo, 2005). Similarly, as we estimate Equation (1.2), the Sanderson-Windmeijer multivariate F statistic equals 53.79, and the Kleibergen-Paap rk LM statistic equals $\chi^2(1) = 54.01$, rejecting the null hypothesis of under-identification indicating that the instrument for $Governance_{i(t-1)}$ is relevant (all at $p < 0.001$). The weak-instrument-robust Anderson-Rubin test statistic for the first stage estimation equals $\chi^2(1) = 19.68$ ($p < 0.001$). Similarly, the Kleibergen-Paap rk Wald F statistic equals 53.79 which provides reassurance regarding weak identification.

1.3.3 Three-Stage Least Square Estimation Procedure

Our full model is a system of two equations where governance quality simultaneously impacts PSR and donations. We also have additional endogenous variables (i.e., fundraising and governance quality) for which we use the aforementioned IVs. Therefore, and since all endogenous variables are jointly determined by the exogenous variables, system estimation methods that offer higher efficiency are more appropriate than single equation estimation approaches (Wooldridge, 2010; Greene, 2012). Moreover, given the set of proposed equations, it is very likely that the error terms of the two equations are correlated. This is expected in systems of equations where one of the explanatory variables in one equation is the dependent variable in another equation, which is the case for PSR in our model. Thus, three-stage least square (3SLS) is a more efficient procedure than the 2SLS, which neglects the correlation between the two equations (Zellner and Theil, 1962). Therefore, we estimate the system of equations 1.1 and 1.2 using 3SLS, instrumenting fundraising expenses and governance quality using the above-mentioned instruments. Figure 1.1 summarizes the analytical approach and reasons why.

1.4 Results, Extension, and Robustness

1.4.1 Main Results

Our results, summarized in Table 1.3, show that a nonprofit's donation income is sensitive to both its PSR and governance quality. The estimate of the coefficient of PSR (governance) in the first column of Table 1.3 shows the percentage change in donations if PSR (governance) changes by 1 percentage point, assuming that everything else, including governance (PSR), remains fixed. We find that a one percentage point increase in PSR, on average, leads to 16.94% [1] increase in donation income (at $p < 0.001$), underlining the importance of PSR. The total effect of governance, reported in Table 1.4, is calculated as the nonlinear combination of the estimates $\alpha_2 + \alpha_1 \times \beta_1$, the combination of the direct effect of governance on donations (i.e., α_2) and its effect through PSR (i.e., $\alpha_1 \times \beta_1$). We observe that a one-point increase in governance, on average, results in 10.11% increase in donation income (at $p = 0.006$). However, as discussed earlier, PSR and governance are not independent. Our results reported in column 2 of Table 1.3 show that a one-point increase in governance is associated with a 0.32 percentage point decrease in PSR (at $p = 0.043$); higher levels of governance are associated with lower PSR. This is consistent with better governance reducing the pressure to report artificially inflated PSRs, as well as the fact that improving governance quality can impose some additional administration costs. The direct effect of governance on donations in column 1 of Table 1.3 shows that as an average organization increases its governance by one point while keeping its PSR constant, its donation income increases by 15.75% (at $p < 0.038$). However, as higher governance quality is accompanied by lower PSR, the total benefit of improved governance declines. We note that our interest is in the overall effects of PSR and governance, not predicting the changes in donations given specific changes in these two variables. Given the structure of our model, the interpretation of the effect sizes is not straightforward.

In addition to PSR and governance, results also highlight the roles of other factors in driving donations. First, results show that fundraising remains as a major driver of donations, verifying previous findings; Fundraising plays the same role for a nonprofit as advertising in the commercial sector (Okten and Weisbrod, 2000) and is nonprofits' predominant strategy to increase donations (Thornton, 2006; Eftekhar *et al.*, 2017).

[1] $100 \times (\exp(0.1565) - 1) = 16.94\%$.

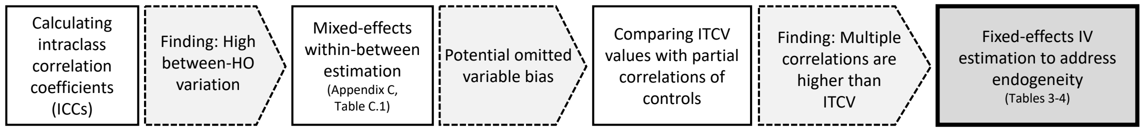

Figure 1.1: Summary of estimation strategy: We started with a mixed-effects method, but then continued our analysis based on a fixed-effects instrumental variable (IV) estimation.

Table 1.3: 3SLS estimation results of the full model. (Numbers in parentheses show standard deviations.)

Dependent variable	$\log(Donations_{it})$	$PSR_{i(t-1)}$
$PSR_{i(t-1)}$	0.1565 (0.0279) [$p < 0.001$]	
$Governance_{i(t-1)}$	0.1463 (0.0381) [$p < 0.001$]	-0.3192 (0.1581) [p=0.043]
$\log(Assets_{i(t-1)})$	-0.2170 (0.0365) [$p < 0.001$]	0.8821 (0.1069) [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0454 (0.0039) [$p < 0.001$]	0.1037 (0.0103) [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.2964 (0.0437) [$p < 0.001$]	1.4061 (0.0660) [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0084 (0.0032) [p=0.008]	0.0213 (0.0132) [p=0.107]
$ProgramConcentration_{i(t-1)}$	0.2063 (0.0796) [p=0.010]	-1.2416 (0.2899) [$p < 0.001$]
$\log(Fundraising_{it})$	0.2652 (0.0419) [$p < 0.001$]	
$ZeroFundraising_{i(t-1)}$		2.6193 (0.1407) [$p < 0.001$]
$LiabilityToAsset_{i(t-1)}$		0.0007 (0.0010) [p=0.470]
$Year_t$	included	included
Observations	174419	174419
χ^2 test	414.9002 [$p < 0.001$]	2255.5088 [$p < 0.001$]

Endogenous variables: $\log(Fundraising_{it})$ and $Governance_{i(t-1)}$; IVs: $\log Occupancy_{it}$ and $GovernanceIV_{i(t-1)}$.

Second, results indicate that earmarking has a significant negative direct impact on donations. On the surface, this finding is contrary to the literature that suggests earmarking is associated with more donations (Nunnenkamp and Ohler, 2012). However, we note that our variable captures the organizations' state, rather than the option they give to new donors. In that regard, our result illustrates that when an organization has a large portion of its resources earmarked, it receives less donations. Since earmarked donations introduce significant challenges for nonprofits (Barman, 2008; Burkart *et al.*, 2016), it is plausible that nonprofits whose assets are more restricted are reluctant to provide an earmarking option which would further restrict

Table 1.4: Total effects of governance and control variables. (Numbers in parentheses show standard deviations.)

Dependent variable	$\log(Donations_{it})$
$Governance_{i(t-1)}$	0.0963 (0.0347) [p= 0.006]
$\log(Assets_{i(t-1)})$	-0.0790 (0.0228) [p= 0.001]
$\log(GovernmentGrants_{i(t-1)})$	-0.0292 (0.0022) [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.0763 (0.0142) [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0051 (0.0029) [p= 0.074]
$ProgramConcentration_{i(t-1)}$	0.0120 (0.0628) [p= 0.848]

the use of their assets. Moreover, donors that prefer to have control over their contributions may perceive that a nonprofit with more earmarked assets is less likely to spend their contributions for the mandate they donate for. Results also show that an increase in earmarked assets is associated with higher PSR, which is expected since earmarked donations mostly restrict expenditures to programs. This increase, however, is smaller than the negative direct effect. Overall, a 1% increase in earmarked assets leads to about 0.51% decrease in donation income (at p=0.074).

Third, results show that program concentration has a positive significant direct effect on donation income. We find, everything else equal, that a nonprofit receives more donations when it concentrates on fewer programs. This suggests a preference in the charitable market towards organizations that specialize in specific programs (Bilodeau and Slivinski, 1997; Penna, 2011). However, as the second column of Table 1.3 shows, on average, nonprofits' PSR falls as they focus on fewer programs. Put differently, diversification of programs enables organizations to spend a higher percentage of their expenses on a larger set of programs. Overall, given the negative impact of this variable on PSR and its direct positive effect on donations, the costs and benefits cancel each other out and the total effect is not significant ($p = 0.848$).

Therefore, our evidence regarding the impact of program concentration on a nonprofit's total donation income remains inconclusive.

1.4.2 First Stage Results: The Effects of Instruments

Table 1.5 reports the coefficients on instruments from the first stage estimates. (Full first stage results are provided in Appendix F.) Similar to Andreoni and Payne (2011), we find that occupancy expenses have a positive significant effect on fundraising. This suggests that as nonprofits expand their operations and infrastructure, they spend more on fundraising. Also, we observe that a one-point increase in $GovernanceIV$, i.e., the average governance of similar nonprofits, leads to a 0.24 point increase in a nonprofit's governance (at $p < 0.001$). This may show that sector-wide norms provide additional incentives for nonprofits to improve their governance. Further, our data show that nonprofits decreased their PSR, on average, by a 0.60 percentage point during 2010–2017 while we find an upward trend in donation income during the same time frame. This is contrary to the increasing trend in PSR levels before the policy change that Lecy and Searing (2015) report, which is a 2.60 percentage point increase over 22 years. This change can at least be partially attributed to the availability of nonprofits' governance information. This finding shows that providing information regarding governance quality has provided nonprofits with a new ground to exhibit their performance and has decreased the overemphasis on PSR.

Table 1.5: Coefficients on instruments from first stage estimation

Dependent variable:	$\log(Fundraising_{it})$	$Governance_{i(t-1)}$
$\log(Occupancy_{it})$	0.4069 [$p < 0.001$]	0.5178 [$p < 0.001$]
$GovernanceIV_{i(t-1)}$	-0.0102 [p=0.258]	0.2254 [$p < 0.001$]
χ^2 test of instruments	87.59 [$p < 0.001$]	138.72 [$p < 0.001$]

1.4.3 Extension: Governance Quality and Potential Misreporting

One mechanism through which better governance can be linked to lower PSR is the reduction of the potential of misreports. Krishnan *et al.* (2006) find reporting zero fundraising expenses is a sign of potential PSR management and misreporting. We compare how often nonprofits in the top and bottom quantiles report zero fundraising expenses. That occurs in 68.40% of the observations from nonprofits whose average governance score is in the bottom 25th percentile of our data, but only in 35.21% of observations in the top 25th percentile. We estimate a mixed-effects logistic model for the probability of reports of zero fundraising expenses, as shown in Equation (1.3).

$$
\begin{aligned}
ZeroFundraising_{it} =& \delta_0 + \sigma_1 \overline{Governance_i} + \sigma_2 \overline{\log(Assets_{it})}_i \\
& + \sigma_3 \overline{\log(GovernmentGrants_{it})}_i + \sigma_4 \overline{\log(OwnIncome_{it})}_i \\
& + \sigma_5 \overline{\log(Earmarked_{it})}_i + \sigma_6 \overline{ProgramConcentration_i} \\
& + \delta_1 \left(Governance_{it} - \overline{Governance_i}\right) \\
& + \delta_2 \left(\log(Assets_{it}) - \overline{\log(Assets_{it})}_i\right) \\
& + \delta_3 \left(\log(GovernmentGrants_{it}) - \overline{\log(GovernmentGrants_{it})}_i\right) \\
& + \delta_4 \left(\log(OwnIncome_{it}) - \overline{\log(OwnIncome_{it})}_i\right) \\
& + \delta_5 \left(\log(Earmarked_{it}) - \overline{\log(Earmarked_{it})}_i\right) \\
& + \delta_6 \left(ProgramConcentration_{it} - \overline{ProgramConcentration_i}\right) \\
& + \phi_t + \mu_{it}.
\end{aligned} \tag{1.3}
$$

Coefficients σ_1 to σ_6 indicate the effects of nonprofit means, i.e., between-nonprofit effects, and coefficients δ_1 to δ_6 show the effects of demeaned variables, i.e., within-nonprofit effects. An advantage of mixed-effects estimation models is that they enable us to explicitly test whether each of the coefficients of the explanatory variables are affected by unobserved heterogeneity. Adding a random component to each of the coefficients accounts for the possible correlation between unobserved heterogeneity and the corresponding explanatory variable. However, this results in losing degrees of freedom. The most common method to decide whether such effects should be added to the model is to include random components in the slopes and use Likelihood Ratio (LR) tests to determine whether the added components are worth retaining in the model. In other words, this test indicates whether the changes in slopes between nonprofits are large enough to make a difference. Moreover, the random components in slopes and in the intercept may covary. Estimating these covariances further decreases degrees of freedom. Therefore, a similar comparison is required to decide whether the covariance(s) must be constrained to zero or must be estimated (Snijders and Bosker, 2012). We therefore include a random component for δ_1. The LR test is significant, indicating that this slope should be random. However, as we include the covariance between this random slope and the intercept, the LR test is not significant, suggesting that an independent covariance structure is preferred.

To ensure that issues of endogeneity due to omitted variables do not bias our inference, we use the robustness of inference to replacement (RIR) which indicates the percentage of the estimates that would need to be biased in order to invalidate causal inference (Busenbark *et al.*, 2022; Frank *et al.*, 2013). We find that 69.21% and 90.46% of the within- and between-nonprofit effects of governance need to be biased to invalidate inference, respectively. We believe this is very unlikely, so the estimation results presented in Table 1.6 are likely to be reliable.

Results indicate that better governance is significantly associated with lower likelihood of reporting zero fundraising expenses, both within and between nonprofits. The within-nonprofit effect of governance indicates that as an average nonprofit increases its governance score by one percent, the odds of reporting zero fundraising expenses decrease by 2.58%. [2] The between effect estimate shows that nonprofits with higher governance scores are less likely to report zero fundraising expenses. The odds of reporting zero fundraising expenses are 7.32% lower for a nonprofit with a governance score that is one percent higher than for a similar nonprofit in terms of all other variables. We note that a contrast test indicates that the within and between effects are significantly different ($\chi^2(1) = 81.72$, $p < 0.001$).

We also find that program concentration is positively associated with the odds of reporting zero fundraising expenses, while the opposite holds for earmarked assets. For both of these variables, we observe a significantly larger effect between nonprofits as compared to within nonprofits. Nevertheless, the within and between effects are in opposite directions for assets, government grants, and own income variables. The within effects show that when a nonprofit grows larger, receives more grants from government entities, and has higher own income, it is less likely to report zero fundraising expenses. However, the between-nonprofit effects suggest that the odds of reporting zero fundraising expenses are higher for larger nonprofits and for those that generally receive more government grants and have higher own income. Since this behavior is an indicator of potential misreporting, this result suggests that misreporting is more prevalent among larger nonprofits that have more income from government grants and their own programs. However, as a nonprofit grows larger and becomes more self-sufficient and more reliant on government grants, it becomes less likely to misreport.

In addition, we find that governance quality has enabled those with reliable reports to differentiate themselves from potential misreporters whose governance quality remained at low levels and even declined. The average governance quality of zero fundraising reporters fell by 4.5 points over the observation period. Moreover, as in-

[2] $100 \times (1 - \exp(-0.0261)) = 2.58\%$.

Table 1.6: Mixed-effects logistic regression estimation results. (Numbers in parentheses show standard deviations.)

Dependent variable: $ZeroFundraising_{it}$	Within-nonprofit	Between-nonprofit
$Governance$	-0.0261 (0.0041) [$p < 0.001$]	-0.0760 (0.0037) [$p < 0.001$]
log($Assets$)	-0.2503 (0.0370) [$p < 0.001$]	0.3420 (0.0272) [$p < 0.001$]
log($GovernmentGrants$)	-0.0238 (0.0064) [$p < 0.001$]	0.0272 (0.0065) [$p < 0.001$]
log($OwnIncome$)	-0.1740 (0.0388) [$p < 0.001$]	0.4987 (0.0294) [$p < 0.001$]
log($Earmarked$)	-0.0324 (0.0061) [$p < 0.001$]	-1.2900 (0.0173) [$p < 0.001$]
$PorgramConcentration$	0.6348 (0.1914) [p=0.001]	3.7053 (0.2210) [$p < 0.001$]
$Year_t$	included	
Intercept	-2.7820 (0.4880) [$p < 0.001$]	
$Var(Governance)$	0.0808 (0.0048)	
$Var(Intercept)$	149.6739 (4.1455)	
Observations	220971	
Nonprofits	38143	
Wald test	16317.5919 [$p < 0.001$]	

Within-nonprofit effects indicate the estimated coefficients of the nonprofit mean values of the variables and between-nonprofit effects indicate the estimated coefficients for nonprofit-centered (demeaned) variables.

dicated in Figure 1.2, the average governance quality of those who reported positive fundraising expenses was consistently higher than those who reported zero fundraising expenses. Further, the difference between the two groups increased over time, making it easier to differentiate them based on their governance score. These further indicate that governance limits nonprofits' ability and/or desire to misreport their expenses and highlight the role of availability of governance information in differentiating between organizations with reliable and unreliable reports.

1.4.4 Robustness Checks

We verified our estimations with a set of robustness checks. First, we excluded organizations that generally report very high or very low PSR. Particularly, we removed organizations whose average PSR levels were in the bottom and top 10th (and 25th) percentiles of the data. Second, we excluded organizations whose reported fundraising expenses in all years of our data equal zero (Andreoni and Payne, 2011). Third,

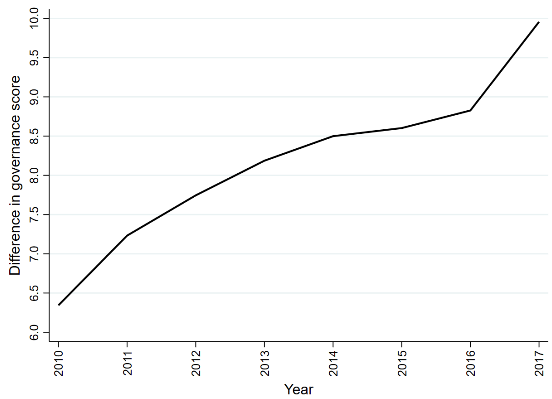

Figure 1.2: Difference between average governance score of nonprofits with positive and zero reported fundraising investments.

similar to Andreoni and Payne (2003), we removed organizations that report zero fundraising expenses more than twice in the observation interval while reporting positive donations in two consecutive years in our data, or have three consecutive years of reporting zero fundraising but positive donations. Fourth, we included observations in the bottom percentile of own income values and observations with negative earmarked assets which we had removed from the main analysis as outliers. Fifth, similar to Andreoni and Payne (2011), we exclude various sub-sectors based on their NTEE codes. Sixth, we explore variations in our instrument for governance quality, including nonlinear terms and adjusting the definition of similar organization categories (e.g., using more granular size categorization, excluding geographical region criteria). Seventh, we use system 2SLS and single equation 2SLS estimation methods for further robustness checks. Estimating the equations separately protects the estimations from potential inconsistency that could be caused by misspecification of one of the equations (Baltagi, 2005). Results of these tests, which indicate that our results are robust, are provided in Appendix E.

1.5 Concluding Remarks

Results of this study reveal that governance quality of nonprofits is now an important driver of donations in addition to their PSR. Therefore, in their strategies for attracting more donations, nonprofit managers need to pay attention to both factors. In fact, we find that enhancing governance quality leads to higher donation income despite the fact that it is generally associated with lower PSR levels. While nonprofits' PSR has commonly been used as a proxy to determine their efficiency (Kinsbergen and Tolsma, 2013; Gneezy *et al.*, 2014), their governance quality provides a new dimension of competition that shows how effectively they use donated resources to solve society's problems. At a higher level, these findings highlight the importance of transparency and information disclosure in nonprofits' strategies. For instance, if a nonprofit increases its overhead costs as it expands its operations to new geographical locations, it can also invest in audits to assure donors that the decrease in PSR is justified and not a result of mismanagement. Similarly, it can transparently disclose detailed information about the additional administrative expenses to try to avoid the negative impact of the resulting lower PSR on donation income.

We find evidence suggesting that mandatory reports on governance quality have helped to mitigate the overemphasis on PSR in evaluating nonprofits and the adverse impacts of this focus. Earlier research found increasing trends in average PSR; in the period since the IRS policy change that made it easier to communicate governance quality information, we find that is no longer the case.

We also find evidence that better governance is associated with lower potential for misreporting, suggesting a mechanism by which governance quality has eased the pressure on PSR. Results indicate existence of competition and sector-wide norms for better governance quality. Namely, as their competitors implement better governance practices, nonprofits attempt to improve their own governance quality. Further, better governance makes nonprofits less likely to report zero fundraising expenses, which is an indicator of PSR management (Krishnan *et al.*, 2006).

Due to unavailability of data before 2008, we are unable to directly measure the impact of the IRS policy change. However, our results suggest that policy makers can help nonprofits to move away from the starvation cycle by increasing transparency and making information about nonprofits more accessible to donors. Similarly, if watchdog organizations provide a more comprehensive picture of nonprofits' governance quality in their evaluations and ratings, donors will likely take that information into account.

This paper has some limitations that offer opportunities for future research. For example, due to concerns of endogeneity, we limited our main analysis to within-nonprofit effects. Future research can implement within-between analysis to compare the effects of PSR and governance within and between nonprofits. Also, we note that, in addition to the IRS publicly available data, nonprofits can use a variety of outlets for voluntary information disclosure (e.g., websites, fundraising materials, media). These elements are ignored in this paper because we are unable to collect information about the channels of data disclosure over the sample period for all organizations in our data set. Moreover, most of the governance quality information required by the IRS is provided in a simple yes-no format. While this provides digestible information to donors and makes it easier to compare nonprofits, it may hide underlying differences among them. For instance, the information indicates whether whistleblower and conflict of interest policies are in place, but it does not reveal the details of these policies. Future research can investigate the differences between the roles of required versus voluntary, and standardized versus detailed governance quality information disclosure. Finally, our data are limited only to years after the IRS policy change, since, previously, nonprofits were not required to file their Forms 990 digitally. It is worth emphasizing that the focus of this paper is to examine the overall value of PSR and governance on a social services organization's donation income when information about both metrics is available. A related question is whether PSR influences donations differently at different levels of governance quality. Our estimation settings do not allow a rigorous analysis of this question. Specifically, we find it necessary to use instrumental variables to ensure that omitted variables do not bias our estimates. We also find that governance has a significant impact on PSR. Therefore, including an interaction term between these two variables in the model increases concerns of endogeneity. We believe future research, and potentially experimental designs, may examine the interaction between these two factors and elaborate other insights.

Chapter 2

APPEARANCE OF EFFICIENCY AT THE EXPENSE OF OTHERS: GRANT PROVISION IN THE NONPROFIT SECTOR

Abstract

Nonprofits are commonly evaluated by financial metrics that value program expenses and, thus, they are encouraged to prioritize strategies that enable them to report higher program expenses. This paper empirically examines the incentives, benefits, and costs of one of these strategies, grant provision, that allows nonprofits to increase their reported program expenses without having to spend their funds on their own programs. Studying the data of 33,847 US-based social services and relief nonprofits during 2010–2017, we find that providing grants to other organizations enables nonprofits to earn more revenue and make a bigger social impact in the long term. We also find that this strategy increases the administrative burden needed to make a social impact and it is especially costly for smaller grant recipient nonprofits. Despite, results suggest that grants are not viewed as less valuable than direct program expenses, highlighting the role of the focus on financial metrics that do not differentiate between these two types of expenses. Results also underline the important roles of resource dependency and revenue volatility in the nonprofit sector, showing that higher dependence on external sources and higher revenue volatility are associated with a greater focus on the grant provision strategy.

2.1 Introduction

The difficulties in measuring nonprofits' ultimate social impact and donors' overhead cost aversion have led to the prevalence of financial metrics in nonprofit performance measurement (Gneezy *et al.*, 2014). These metrics mainly evaluate nonprofits based on how they use their resources and, therefore, influence how nonprofits allocate their budgets (Beamon and Balcik, 2008). Generally, nonprofits that spend more on their programs are considered to have better performance and are able to earn more donations (Parsa *et al.*, 2022). As a result, nonprofit managers prioritize budget allocation strategies that enable them to report higher program expenses. One of these strategies is to allocate a part of the budget to grants provided to other nonprofits. Since these transactions are categorized as program expenses, this strategy can help the nonprofit to appear more efficient when evaluated by the prevalent financial metrics (Arya and Mittendorf, 2016).

If donors, who rely on financial metrics, do not differentiate between the budget spent directly on a nonprofit's core programs and grants reported as program expenses, this grant provision strategy can enable a nonprofit to earn more revenue (Arya and Mittendorf, 2016). However, empirical findings suggest that donors may be sensitive to "how" their donations are spent beyond the financial metrics that simply show "how much" of the resources are spent on programs (Parsa *et al.*, 2022). In fact, one of the reasons that donors value program expenses is their preference to make a direct impact on beneficiaries' lives (Duncan, 2004). While grants can create an appearance of higher efficiency, they decrease the perceived direct impact by creating an additional layer between donors and beneficiaries. Further, a longer supply chain increases the administrative burden required to make a social impact (Arya and Mittendorf, 2016), thus making this strategy less appealing to donors. Therefore, the actual benefits of the grant provision strategy for nonprofits remain unclear. The goal of this paper is to empirically investigate whether the grant provision strategy is beneficial for nonprofits' long-term revenue and impact.

As resource dependent entities, the extent to which nonprofits implement strategies such as grant provision can be largely attributed to the external pressures they receive from their external sources of revenue (Pfeffer and Salancik, 2003; Eftekhar *et al.*, 2017). In that regard, we note that the pressures imposed by the wide use of financial metrics make nonprofits reluctant to reserve their extra funds for future use (Calabrese, 2018). Grant provision, therefore, can be a particularly attractive strategy when nonprofits have funds beyond their operational capacities, e.g., when they observe a sharp increase in their revenue. Therefore, and in order to move towards a better understanding of the use of this strategy in the sector, we also investigate the effects of dependence on external resources and revenue volatility on nonprofits' use of the grant provision strategy.

We focus our analysis on nonprofits in social services and relief. In addition to their large contribution to the nonprofits sector, these nonprofits have a higher dependence on external sources of revenue than other nonprofits whose core programs generate large amounts of revenue (Parsa *et al.*, 2022). Therefore, they are particularly under pressure to report higher program expenses and, therefore, they are more likely to use the grant provision strategy (Arya and Mittendorf, 2016). Given the difficulty to measure nonprofits' actual impact, we consider their total revenue as a measure of their ability to support their core missions.

Our results confirm the benefits of the grant provision strategy for nonprofits. We find that providing grants to other organizations leads to higher revenue, not only in the short term, but also in the long run. Moreover, results suggest that, by allowing nonprofits to earn more revenue, this strategy enables them to make a bigger social impact in the long term. We do not find any evidence that grants are viewed as less valuable than direct program expenses, suggesting that the widespread focus on financial metrics that do not differentiate between these two types of expenses has contributed to the nonprofits' tendency to use this strategy. Results also show that higher dependence on external sources is associated with a greater focus on the grant provision strategy. Moreover, we find that nonprofits that use this strategy provide more grants to other organizations when they observe sharp increases in their revenue. Finally, results confirm that this strategy increases the administrative burden to make social impact. We find that as nonprofits receive more grants, their administrative costs increase. Grants are particularly expensive in administrative burden when the recipients are smaller organizations.

While the extant literature documents a pressure on nonprofits to increase their program expenses, budget allocation strategies that nonprofits use to achieve higher levels of program spending have not been investigated. Specifically, to our knowledge, Arya and Mittendorf (2016) is the only study that considers the grant provision strategy and analytically shows its potential benefits for nonprofits. In this paper, we provide empirical evidence for the benefits and costs of this strategy for the nonprofit sector. Moreover, the literature highlights the focus on financial metrics as the main incentive for this strategy, but the factors that contribute to more grant provision remain unknown. This paper provides insights in that regard showing that dependence on external sources and sudden increases in revenue can contribute to a greater focus on this strategy. We further contribute to the literature by demonstrating potential ways to help the nonprofit sector avoid the cycle of overheads that grant provision can impose. Our findings suggest that nonprofits should follow a consistent plan for grant provision, such that the recipients expect the grants ahead of time and can plan for an efficient use of the grants. Further, results suggest that nonprofits should consider the operational capacity of their grant recipients and avoid giving grants to smaller organizations without ensuring their need for grants and their ability to efficiently utilize them. Finally, it has been shown that donors consider information other than simple financial metrics in evaluating nonprofits (Parsa *et al.*, 2022). Our findings suggest that mere availability of information may not be enough to make it influential on nonprofits' revenue. This calls for actions from policy makers and watchdog organizations that can emphasize and draw attention to such factors.

2.2 Literature and Hypotheses

Given the nature of their operations and the variety of the services that nonprofits provide, it is difficult to develop global and easily measurable metrics to evaluate their performance (Beamon and Balcik, 2008; Eftekhar *et al.*, 2017). Therefore, financial metrics such as program spending ratio (PSR), that is the ratio between program expenses and total expenses, have become the predominant performance measures in the sector (Exley, 2020). These metrics mainly evaluate how a nonprofit allocates its budget to its programs and overhead costs (administrative and fundraising expenses) and depict those with higher program expenses as better performers (Gneezy *et al.*, 2014). Therefore, and as supported by experimental and empirical evidence, reporting higher levels of program expenses helps nonprofits to attract more revenue (Exley, 2020; Parsa *et al.*, 2022). This focus pressures nonprofits to use strategies that enable them to report higher program expenses, including cutting necessary overhead expenses and even misreporting their financials (e.g., by reporting fundraising expenses as program expenses) (Gregory and Howard, 2009; Krishnan *et al.*, 2006). One strategy that allows nonprofits to increase their reported program expenses without having to spend their funds on their own programs is to allocate a part of their budgets to grants provided to other organizations. In financial forms like Form 990, that are the main source of information about nonprofits, these grants are categorized as program expenses. Therefore, by creating an appearance of higher efficiency as measured by the common financial metrics, this strategy can enable nonprofits to increase their revenue (Arya and Mittendorf, 2016).

Recent studies have shown that donors may not solely rely on financial metrics and they are also sensitive to more detailed information about nonprofits, such as their governance quality (Parsa *et al.*, 2022). In that regard, we note that while grants are categorized as program expenses, in publicly available financial forms such as Form 990, donors can observe the breakdown of what amounts to the total program expenses reported, including the amounts of grants provided to other organizations. Therefore, it is expected that at least some of the donors and grantors differentiate between different types of expenses that are reported as program expenses. It is important to note that one of the main reasons that donors are sensitive to program expenses is their preference to make a direct impact on beneficiaries' lives (Duncan, 2004; Gneezy *et al.*, 2014). Grants create an additional layer between donors and beneficiaries and therefore decrease the perceived direct impact. Moreover, the additional layers and the longer supply chain resulted by these grants also create a higher level of overhead costs needed to make the social impact (Arya and Mittendorf, 2016). Therefore, and given that donors prefer lower overhead costs (Gneezy *et al.*, 2014), they are expected to see less value in grants than in direct program expenses.

Hypothesis 1a *Providing more grants to other organizations is associated with higher revenue for nonprofits.*

Hypothesis 1b *Providing grants to other organizations has a smaller effect on non-profits' revenue than direct expenses on programs.*

The ultimate goal of nonprofits, especially social services and relief organizations, is to serve their core missions and to make social impact, rather than to maximize their revenue (Steinberg, 1986). Therefore, it is unlikely that they extensively use the grant provision strategy unless they have incentives to do so. In that regard, we note that nonprofits depend considerably on external sources, and this dependence influences how they make strategic and operational decisions (Carroll and Stater, 2009; Verschuere and De Corte, 2014; Eftekhar *et al.*, 2017). From this perspective, the main incentive for this strategy is the reliance of external sources of income on financial metrics that allow nonprofits to appear more efficient by increasing their program expenses through grant provision. As a result, it is expected that higher dependence on donors and grantors, who use these metrics to evaluate nonprofits, leads to a more extensive use of this strategy (Arya and Mittendorf, 2016).

The use of the grant provision strategy can also be attributed to the high levels of volatility in nonprofits' budgets which significantly influence how nonprofits operate, including how they make budget allocation decisions (Berenguer and Shen, 2020). Nonprofits generally plan for their expenses in the beginning of a year given their operational capacity and their expected revenue during that year (Ebdon, 2021). If, for instance, they earn less revenue than expected, they use their reserves to fill the gap between their budget and their planned expenses (Calabrese, 2018). On the contrary, if a nonprofit experiences a sudden increase in their revenue, they can save the funds as reserve for future use. However, as a result of the pressures imposed by the use of financial metrics, nonprofit managers value current spending more than reserving funds for the future (Calabrese, 2018). Also, given their operational capacity, they may find it difficult to use these funds directly on their own programs. Doing so may require expanding the scope and scale of their operations which may not be feasible during a single year and also requires additional administrative costs (Parsa *et al.*, 2022).

Hypothesis 2a *Nonprofits provide more grants to other organizations when they depend more on donations and grants.*

Hypothesis 2b *Nonprofits provide more grants to other organizations when they experience large increases in their revenue.*

2.3 Data

We use a dataset containing information of US-based nonprofits in social services and relief during 2010-2017, as described in Parsa *et al.* (2022). We note that nonprofits whose main mission is to raise and distribute funds for multiple organizations are excluded from this dataset. Nonprofits in the data provide services such as assisting human trafficking survivors, marginalized groups, and people with disabilities, advocating for human rights and women's rights, and disaster preparedness and relief.

The data are extracted from digitally filed and publicly available Forms 990, the primary source of information about nonprofits in the US (Harris *et al.*, 2015). These forms contain general and financial information about nonprofits, including their missions, board members, main programs, as well as revenue from different sources, expenses (categorized as program, fundraising, and administrative expenses), assets, and liabilities. In the Statement of Functional Expenses in these forms, nonprofits report a breakdown of different types of expenses that includes the grants they provided to other organizations. We therefore further collected these data that make up the main variable for our analysis.

In line with the existing literature (e.g., Andreoni and Payne (2003) and Andreoni and Payne (2011)), the data excludes very large organizations (with average total expenses more than USD 50 million), nonprofits that reported no income from public donations in all years of observation, observations with non-positive total expenses, non-positive assets, negative program expenses, program expenses more than total expenses, negative fundraising expenses, non-positive revenue, negative public donations, negative government grants, negative earmarked assets, negative fixed assets, and outliers with very large losses in own income. We further removed observations with negative reported grants and those with extreme annual changes in revenue. Finally, we exclude nonprofits with fewer than 4 years of data. Our final dataset includes 206,409 organization-year observations of 33,847 nonprofits.

2.4 Methods

2.4.1 Nonprofits' Revenue

We estimate Equation (2.1) to examine the effects hypothesized in Hypotheses 1a and 1b,

$$\begin{aligned}\sinh^{-1}(Revenue_{it}) = &\alpha_1 \sinh^{-1}(Grants_{i(t-1)}) + \alpha_2 \sinh^{-1}(ProgramExpenses_{i(t-1)}) \\ &+ \alpha_3 X_{it} + \phi_t + v_i + u_{it},\end{aligned} \tag{2.1}$$

where the dependent variable is the inverse hyperbolic sine (IHS) of *total revenue* that is the nonprofits' revenue from donations, grants, and own income (that is income from program and service revenue, investment, and other income). We have two main explanatory variables: the IHS of the total amount of *grants* provided to other organizations in the US as reported in the Statement of Functional Expenses of Form 990, and the IHS of *program expenses* that represents the reported total program expenses excluding grants. Since an important premise of this research is the external pressure on nonprofits to report high program expenses, and these data are generally made available to the public after a year, we use a 1-year lag for these variables.

We also include a set of control variables, X_{it}, in our model. First, maintaining reserves is an alternative strategy for nonprofits' growth in the long term and can also be influenced by external pressures to increase program expenses (Calabrese, 2013; Kim and Mason, 2020). Therefore, we include the IHS of nonprofits' *reserves* calculated as liquid unrestricted net assets which represents the amounts of cash, receivables, and liquid investments that are not earmarked for specific purposes (Nonprofit Operating Reserves Initiative Workgroup, 2008; Bowman, 2011). Second, similar to other studies in this area (e.g., Calabrese (2013) and Eftekhar *et al.* (2017)), we control for the nonprofits' size that we capture by the IHS of the nonprofits' *fixed assets* in the given year which includes land, buildings, and equipment. Fixed assets are less likely to be influenced by financial distress and therefore can represent the nonprofit's general ability to operate regardless of the external financial pressures (Denison, 2009). Third, given donors' preference to earmark their donations to assert more control over their use, earmarking is associated with higher revenue (Nunnenkamp and Ohler, 2012). On the other hand, these restrictions make nonprofits vulnerable to financial shocks (Calabrese, 2018). We therefore control for the IHS of nonprofits' *earmarked assets*, calculated as the total of temporarily and permanently restricted net assets. Fourth, given the importance of the pressures from external sources in our research context, we further control for the nonprofits' *donation dependence* and *government dependence* which are calculated as the percentage of the nonprofits' revenue from donations and government grants, respectively. Level of dependence on donations is associated with nonprofits' volatility (Carroll and Stater, 2009). Government grants are also an important source of revenue for nonprofits and can significantly influence their financial status and decisions (Andreoni and Payne, 2011; Parsa *et al.*, 2022). Fifth, nonprofits' fundraising efforts are considered as a significant driver of donations to nonprofits (Okten and Weisbrod, 2000; Thornton, 2006). Thus, we also control for the IHS of *fundraising expenses*. Sixth, the heterogeneity of donor preferences for different programs (Rose-Ackerman, 1982), and on the contrary, their preference for specialized nonprofits that focus on specific programs (Penna, 2011), make *program concentration* an important control variable in our settings. Therefore, similar to Parsa *et al.* (2022), we control for this factor using the Herfindahl-Hirschman index (HHI) of the nonprofits' expenses on their main programs as reported on Form 990. This variable ranges between zero and one, where an HHI equal to 1 shows perfect concentration on a single program. Seventh, *revenue concentration* is an important factor when studying nonprofits' financial status (Bowman, 2011; Hung and Hager, 2019). Therefore, we control for the HHI of the nonprofits' revenue from the three main sources of donations, government grants, and own income (Carroll and Stater, 2009). Finally, given the panel structure of our data which contain multiple observations per nonprofit and can cause correlated errors, we account for all observed and unobserved time-invariant differences between nonprofits by including organization fixed effects. Year dummies are also included in the model to account for time fixed effects.

In line with the literature (e.g., Mendoza-Abarca and Gras (2019) and Parsa *et al.* (2022)) and given the wide range of nonprofits' size in our dataset, we transform the variables that are measured in USD. We use the IHS transformation, $\sinh^{-1}(x) = \log(x + (x^2 + 1)^{\frac{1}{2}})$, which approximates the log function and is preferred to the log function when the data include meaningful zero and negative values (Burbidge *et al.*, 1988; Jayachandran *et al.*, 2017; Ammann and Schaub, 2021). This is the case for two of the variables in our dataset, reserves and grants. It is not uncommon for nonprofits to have negative reserves (Nonprofit Operating Reserves Initiative Workgroup, 2008; Calabrese, 2018). In our data, about 21% of the observations include negative values for reserves. Also, about 85% of the observations in our data report zero grants provided to other organizations. We note that for positive values, the log-transformed variables and the IHS-transformed variables have perfect correlation. Further, for variables with large average values, the coefficients can be interpreted similar to log-transformed variables (Bellemare and Wichman, 2020).

Endogeneity

A fixed-effects (FE) estimation of Equation (2.1) is likely to be biased due to existence of omitted variables. Specifically, we are concerned that factors that are not observed in our data may simultaneously impact the main variable of interest, grants, and the dependent variable, thus making this variable endogenous. For example, a nonprofit's board composition and characteristics can impact its revenue and, at the same time, its budget allocation decisions like grant provision. Another example is a sudden increase in the demand for the services that a nonprofit provides. For instance, the Red Cross received "an outpouring of donations" after the Haiti earthquake and at the same time provided a significant amount of grants to other organizations active in Haiti response (Elliott and Sullivan, 2015). Although the time lag considered in our model protects against some of these confounding factors, the potential of endogeneity remains.

Instrumental variable (IV) approaches are the common methods to address endogeneity. However, these methods can in fact lead to more bias (Larcker and Rusticus, 2010; Busenbark *et al.*, 2022). Therefore, we first implement an FE estimation for Equation (2.1) and apply the *impact threshold of a confounding variable* (ITCV) (Frank, 2000) to investigate whether omitted variable bias is likely to invalidate causal inference from our results. The ITCV informs us of the minimum correlations between an omitted variable and the independent and dependent variables needed to alter the causal inference of a coefficient at a certain p-value (Frank, 2000). We therefore calculate the ITCV value for coefficient α_1 in Equation (2.1) and compare that against the partial correlations of our control variables with revenue and grants. It is suggested to use IV methods if several control variables have correlations with the independent and dependent variables that exceed the ITCV value (Busenbark *et al.*, 2022).

In our FE estimates, partial correlations of multiple control variables are higher than the ITCV value for grants, which equals 0.085 at $p = 0.10$. This means that if the square root of the product of partial correlations of an omitted variable with revenue and grants is higher than 0.085, the statistical inference that this coefficient is different from zero at $p = 0.10$ is biased. This condition holds for three out of eight control variables in our model. For instance, partial correlations of earmarked assets with revenue and grants equal 0.255 and 0.113, respectively. The square root of the product of these partial correlations equals 0.170 and is considerably higher than the ITCV value for grants, 0.085. Therefore, we conclude that the FE estimates are likely to be biased.

In our settings, it is difficult to find exogenous variables that satisfy the conditions for valid IVs, i.e., variables that are correlated with grants but do not have a direct effect on nonprofits' revenue. Occupancy expenses and liabilities, that indicate financial security of a nonprofit, are instruments that are used in other studies in this field (Andreoni and Payne, 2011; Parsa *et al.*, 2022). The dependent variable in these studies is the nonprofits' donation income. Andreoni and Payne (2011) argue that donors are unlikely to be informed of the nonprofits' financial security when they make their donations, supporting the second condition for a valid IV. In this paper, however, we are interested in the nonprofits' overall financial status and, therefore, consider their total revenue as the dependent variable. This variable includes government grants and nonprofits' own income in addition to donations. The aforementioned argument is unlikely to hold for these sources. For instance, government grants are given following closer inspections and audits and provided that nonprofits meet certain criteria (Andreoni and Payne, 2003). Therefore, it is likely that government entities consider a nonprofit's financial security as a precondition for grants. Furthermore, a nonprofit's own income is expected to be strongly correlated with its financial security. In our data, pairwise correlations of occupancy expenses and liabilities with revenue equal 0.503 and 0.633, while their pairwise correlations with donations equal 0.120 and 0.072, respectively. Although high correlations do not necessarily signify direct effects, this observation further questions the validity of these variables as IVs in our model.

The literature also suggests using IVs that capture the sector conditions. For instance, Newton (2015) uses an IV that calculates the average performance of nonprofits that are similar in size, sector, and location. Parsa *et al.* (2022) uses a similar IV for nonprofits' governance quality. Therefore, we can follow this approach and create an IV that, for each nonprofit in a given year, calculates the average amount of grants that nonprofits in the same sector, size category, and geographical region provided to other organizations in that year. Theoretically, it is reasonable to assume that similar nonprofits use the grant provision strategy at a comparable level. A nonprofit finds this strategy more appealing if it is a common practice for peer organizations in the same sector and location. However, it is not reasonable to argue that the average amounts of grants given by similar nonprofits is not correlated with a nonprofit's revenue since the nonprofit may in fact be the recipient of some of these grants. Further, in our data, this variable is only weakly correlated with grants. The pairwise correlation between these two variables equals 0.098. If we disregard the aforementioned concerns and use this variable as an IV, the Kleibergen-Paap rk LM statistic equals $\chi^2(1) = 5.10$, rejecting the null hypothesis of under-identification at

$p = 0.024$ (Kleibergen and Paap, 2006). However, the Kleibergen-Paap rk Wald F statistic equals 5.00 which warns us about weak identification that can lead to more bias (Stock and Yogo, 2005). Therefore, this variable is not a valid IV since it is only weakly correlated with the potential endogenous variable and is also likely to be correlated with the dependent variable. We note that, for a two stage least square (2SLS) estimation using this IV, the Anderson-Rubin test statistic, that is robust to weak instruments, equals $\chi^2(1) = 3.63$ and suggests that the effect of our potentially endogenous variable, grants, is significantly different from zero at $p = 0.056$ (Anderson and Rubin, 1949).

Since external valid IVs are not available in our settings, we apply the heteroskedasticity based IV (HBIV) approach developed by Lewbel (2012). This technique is suggested in these situations since it does not rely on external IVs and, instead, generates internal IVs using heteroskedastic errors of the first stage estimation. This approach is shown to be effective in addressing endogeneity under mild assumptions (Assaf and Tsionas, 2021; Quiroga, 2021) and has been used in recent studies in the absence of external IVs (Anderson and Core, 2018; Agca *et al.*, 2021; Hasan *et al.*, 2021). As Figure 2.1 shows, in our data, the residuals of the first stage estimate are heteroskedastic which supports the use of the HBIV method (Baum and Lewbel, 2019). We further use the Hansen (1982) test to verify the validity of the instruments generated by this method (Anderson and Core, 2018; Baum and Lewbel, 2019). The Hansen J statistic equals $\chi^2(14) = 18.744$ ($p = 0.175$), failing to reject the null hypothesis that the instruments are valid. Similarly, the Kleibergen-Paap rk Wald F statistic equals 12.76 ensuring that weak identification is not a concern (Stock and Yogo, 2005). (Results of the FE estimation without IVs, 2SLS IV estimation using the aforementioned external IV, and HBIV estimates using both the external IV and heteroskedasticity based IVs are reported in Appendix G.)

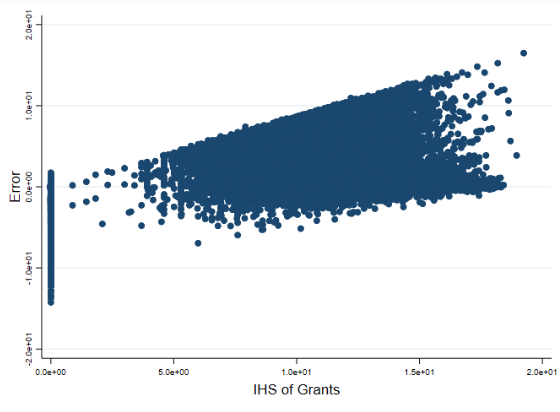

Figure 2.1: Scatterplot of the residuals and grants indicate heteroskedasticity in the first stage estimates

2.4.2 Grant Provision

We estimate Equation (2.2) to examine the effects hypothesized in Hypotheses 2a and 2b,

$$\begin{aligned} Grants_{it} = &\beta_1 DonationDependence_{it} + \beta_2 GovernmentDependence_{it} \\ &+ \beta_3 RevenueGrowth_{it} + \beta_4 Y_{it} + \gamma_t + \epsilon_{it} \end{aligned} \tag{2.2}$$

where the dependent variable is the amount of *grants* provided to other organizations. The main explanatory variables are *donation dependence* and *government dependence* that are defined as in Section 2.4.1, as well as *revenue growth*, which is the percentage change in the nonptofit's revenue from the year before. Similar to Equation (2.1) and since these variables are important when considering nonprofits' budget allocation decisions, we include a set of control variables, Y_{it}, that includes IHS of *reserves*, IHS of *fixed assets*, IHS of *earmarked assets*, IHS of *fundraising expenses*, *program concentration*, and *revenue concentration*. Further, as discussed, grant provision could be used as an alternative to expenses on core programs. Therefore, we also control for the IHS of the nonprofits' *program expenses*. Finally, we account for time fixed effects by including year dummies in the model. Descriptive statistics and correlations of the variables are provided in Tables 2.1 and 2.2, respectively.

Table 2.1: Summary statistics and descriptions of variables

Variable	Description	Mean	SD	Min	Max
$\sinh^{-1}$ *Revenue*	Inverse hyperbolic sine (IHS) of total revenue	14.399	1.663	0.881	19.424
$\sinh^{-1}$(*Grants*)	IHS of total grants provided to other organizations in the US	1.759	4.308	0.000	19.238
$\sinh^{-1}$(*ProgramExpenses*)	IHS of total program expenses excluding grants provided to other organizations	13.809	2.629	0.000	19.133
$\sinh^{-1}$(*Reserves*)	IHS of liquid unrestricted net assets	7.343	11.017	-18.715	20.920
$\sinh^{-1}$(*FixedAssets*)	IHS of fixed assets (land, buildings, and equipment)	11.217	5.375	0.000	20.579
$\sinh^{-1}$(*Earmarked*)	IHS of total temporarily and permanently restricted assets	5.995	6.531	0.000	19.738
DonationDependence	Percentage of revenue from donations	36.095	35.623	0.000	100.186
GovernmentDependence	Percentage of revenue from grants	22.615	32.092	0.000	99.722
$\sinh^{-1}$(*Fundraising*)	IHS of fundraising expenses	5.573	5.609	0.000	17.044
ProgramConcentration	HHI index of the expenses on reported programs	0.807	0.268	0.000	1.000
RevenueConcentration	HHI index of the revenue from donations, government grants, and own income	0.718	0.204	0.333	1.000
RevenueGrowth	Annual percentage change in revenue	10.515	55.435	-89.996	900.000

Table 2.2: Correlations of variables used in estimation model

		1	2	3	4	5	6	7	8	9	10	11	12
1	$\sinh^{-1}$ *Revenue*	1.000											
2	$\sinh^{-1}$(*Grants*)	0.057	1.000										
3	$\sinh^{-1}$(*ProgramExpenses*)	0.714	-0.199	1.000									
4	$\sinh^{-1}$(*Reserves*)	0.143	0.059	0.084	1.000								
5	$\sinh^{-1}$(*FixedAssets*)	0.479	-0.171	0.473	-0.067	1.000							
6	$\sinh^{-1}$(*Earmarked*)	0.415	0.078	0.282	0.125	0.252	1.000						
7	*DonationDependence*	-0.308	0.170	-0.319	0.015	-0.300	0.009	1.000					
8	*GovernmentDependence*	0.110	-0.085	0.147	0.033	0.072	0.017	-0.407	1.000				
9	$\sinh^{-1}$(*Fundraising*)	0.300	0.061	0.218	0.147	0.162	0.399	0.201	-0.058	1.000			
10	*ProgramConcentration*	-0.315	-0.067	-0.249	-0.078	-0.131	-0.271	0.043	-0.103	-0.233	1.000		
11	*RevenueConcentration*	0.095	0.065	0.018	-0.043	-0.084	-0.150	0.062	-0.228	-0.188	0.119	1.000	
12	*RevenueGrowth*	0.040	0.035	-0.053	-0.013	-0.056	-0.009	0.084	-0.030	0.009	0.030	0.022	1.000

To estimate Equation (2.2), we note that the dependent variable takes the value of zero in a large portion of our data. More importantly, a large number of the nonprofits in our data never report any grants provided to other organizations. Specifically, out of 33,847 nonprofits in our data, the value of grants equals zero for all years of observation for 25,509 nonprofits. In other words, the dependent variable has no variation within these nonprofits. Therefore, an FE estimation of the model eliminates more than 75% of our dataset from the analysis and, consequently, it is not an ideal approach in our settings. This makes the generalized estimating equation (GEE) the preferred method which has been used by other researchers under similar circumstances (e.g., Sine *et al.* (2003) and Shah *et al.* (2017)). Developed by Liang and Zeger (1986), GEE is an extension of generalized linear models (GLM) to panel data estimation which does not assume normal distribution for the dependent variable. Further, observations do not need to be independent and can be correlated or clustered (Shah *et al.*, 2017). GEE requires specification of the distribution of the dependent variable, the link function, and the correlation structure and allows for computing robust standard errors that are valid even with misspecified correlation structures (Greene, 2012; Rhee *et al.*, 2006). Therefore, similar to Wowak *et al.* (2015) and Shah *et al.* (2017) we use a GEE model with a log link function (hence the non-transformed dependent variable) and an exchangeable correlation matrix. Our dependent variable is continuous and, thus, we use a Gaussian distribution similar to Rhee *et al.* (2006). In addition to the GEE estimations, we also report FE estimations of the model with the IHS-transformed dependent variable. We note that the FE estimations indicate the effects for a subset of nonprofits that provided grants to other organizations at least in one year during the observation period.

2.5 Results

2.5.1 Nonprofits' Revenue

Results of the HBIV estimation of Equation (2.1) are reported in Table 2.3. The coefficient estimate for grants is positive and significant (at $p < 0.001$) which provides support for Hypothesis 1a. We find that as a nonprofit provides more grants to other organizations, its revenue increases. Similarly, allocating more funds to direct program expenses leads to more revenue (significant at $p < 0.001$). A one percent increase in grants, on average, leads to an approximate 1.53% [1] increase in revenue, and for a one percent increase in direct program expenses, a nonprofit observes an average increase of 4.08% in its revenue. These results provide support regarding the existence of pressures on nonprofits that make it beneficial for them to increase their reported program expenses, either through allocating their budgets directly to their core programs or by providing grants to other organizations.

Table 2.3: Heteroskedasticity-based instrumental variable (HBIV) estimation results for revenue. (Numbers in parentheses show robust standard deviations.)

Dependent variable	$\sinh^{-1} Revenue_{it}$
$\sinh^{-1}(Grants_{i(t-1)})$	0.0152 (0.0038) [$p < 0.001$]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0400 (0.0022) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0003 (0.0002) [p=0.139]
$\sinh^{-1}(FixedAssets_{it})$	0.0106 (0.0009) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0033 (0.0004) [$p < 0.001$]
$DonationDependence_{it}$	0.0027 (0.0002) [$p < 0.001$]
$GovernmentDependence_{it}$	0.0038 (0.0002) [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0115 (0.0005) [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0827 (0.0143) [$p < 0.001$]
$RevenueConcentration_{it}$	0.2209 (0.0159) [$p < 0.001$]
$Year_t$	included
Observations	163308
F test	330.3709 [$p < 0.001$]
Underidentification test	157.4502 [$p < 0.001$]
Hansen J test	18.7436 [p=0.1750]

$\sinh^{-1}(Grants_{i(t-1)})$ is treated as endogenous.

While the point estimate for the effect of program expenses is significantly higher than that of grants (at $p < 0.001$), we note that nonprofits generally spend a smaller portion of their budgets on grants than on program expenses. In our data, on average, about 4.50% and 78.92% of a nonprofit's expenses are spent on grants and core programs, respectively. Therefore, allocation of a certain amount of funds leads to a larger percentage change in grants than in program expenses. Thus, we cannot solely rely on the estimates of α_1 and α_2 to conclude whether providing grants to

[1] $100 \times (\exp(0.0152) - 1) = 1.53\%$.

other organizations leads to smaller benefits than expenditures on direct programs (Hypothesis 1b). For this purpose, we perform a counterfactual analysis to compare the nonprofits' actual budget allocation with a counterfactual scenario where, instead of providing grants to other organizations, they allocate those funds to their core programs. Hypothesis 1b suggests that nonprofits' revenue would increase if they follow this counterfactual budget allocation policy.

We note that the estimation results of Equation (2.1) indicate that as a nonprofit allocates more funds to its programs and grants in year t, it is able to earn more revenue after this information is made available to the public in the next year, i.e., in year $t+1$. More revenue in year $t+1$, in turn, means that the nonprofit has more available funds to allocate to its programs and grants in year $t+1$. Therefore, we use the Stata package "forecast" that allows us to perform dynamic forecasts including additional equations that capture these relationships. A dynamic forecast requires a balanced dataset. Therefore, we create a balanced subset of our data which includes 11,595 nonprofits with data for all the years 2010 through 2016. This is the largest possible balanced dataset from our data. We note that, in addition to their revenue, nonprofits can use their reserves to increase their expenses in a year (Calabrese, 2018). We further note that there are four variables on the right hand side of Equation (2.1) that indicate nonprofits' budget allocation decisions: grants, program expenses, fundraising expenses, and reserves. Therefore, we define a nonprofit's budget in a given year as the summation of its revenue and reserves, $Budget_{it} = Revenue_{it} + Reserves_{it}$. We also define a nonprofit's budget allocation policy as the fraction of the budget allocated to these four categories. Let us denote nonprofit i's actual budget allocation policy in year t as $A_{it} = \{G_{it}, P_{it}, F_{it}, R_{it}\}$, where $G_{it} = \frac{Grants_{it}}{Budget_{it}}$, $P_{it} = \frac{ProgramExpenses_{it}}{Budget_{it}}$, $F_{it} = \frac{Fundraising_{it}}{Budget_{it}}$, and $R_{it} = \frac{Reserves_{it}}{Budget_{it}}$. In the baseline scenario, each nonprofit follows its actual budget allocation policy, A_{it}, and allocates the same fractions of its predicted budget, which includes its predicted revenue from HBIV estimates of Equation (2.1), to these four categories. In the counterfactual scenario, on the other hand, the nonprofit allocates its predicted budget following the counterfactual budget allocation policy $A_{Cit} = \{G_{Cit}, P_{Cit}, F_{it}, R_{it}\}$, where $G_{Cit} = 0$ and $P_{Cit} = G_{it} + P_{it}$.

To compare the baseline and counterfactual scenarios, we calculated total predicted revenue and total program expenses for each nonprofit over the years 2010 through 2016. We note that nonprofits which never provide any grants to other organizations, i.e., those for which $G_{it} = 0, \forall t \in \{2010, \ldots, 2016\}$, the two scenarios are identical. Contrary to our expectation from Hypothesis 1b, among 2,664 nonprofits that provided grants to other organizations in at least one year of observation, the counterfactual scenario leads to a lower (higher) total revenue than the baseline scenario for 2,505 (159) nonprofits. Figure 2.2 shows the histogram of the percentage change in total revenue of these nonprofits in the counterfactual scenario as compared to the baseline scenario. Further, we find that the counterfactual scenario leads to lower total direct program expenses for 1,752 nonprofits as compared to 1,060 nonprofits whose total direct program expenses increase. As program expenses are commonly used to evaluate a nonprofit's social impact, this finding illustrates that grant provision to other organizations can in fact enable a nonprofit to make a bigger social impact in the long term. We note that, in the counterfactual scenario, we assume that nonprofits have the operational capacity to efficiently reallocate their grants to their own programs. In practice, nonprofits are unlikely to be able to spend all of the grants on their own programs. Therefore, benefits observed in our counterfactual analysis are upper bounds for actual benefits. These findings highlight the magnitude of the effect of grants on nonprofits' revenue and provide support for the assumption that nonprofits' external sources of revenue do not view grants as less valuable than direct program expenses. Parsa *et al.* (2022) find that, in addition to financial metrics, donors are also sensitive to information such as nonprofits' governance quality. They highlight that the Internal Revenue Service (IRS) policy change in 2008 drew attention to these factors such that, for instance, Charity Navigator added criteria to its method for evaluating nonprofits. In that regard, we note that the current methods for rating nonprofits do not explicitly differentiate grant provision from program expenses. Therefore, our findings suggest that mere availability of information may not be enough to make a difference. As it is costly and time consuming for donors to investigate detailed information about nonprofits (Hope Consulting, 2010; Balsam and Harris, 2014), they are likely to rely on ratings and factors that are highlighted by watchdog organizations and sector policy makers.

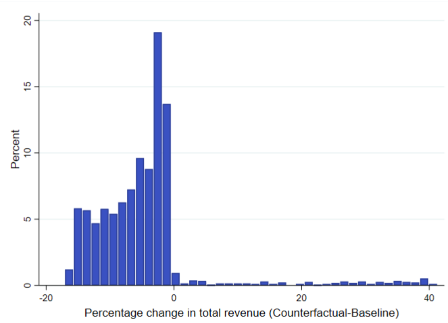

Figure 2.2: Histogram of the percentage change in total revenue in the counterfactual scenario as compared to the baseline scenario for nonprofits that provided grants to other organizations in at least one year of observation

Results reported in Table 2.3 also indicate that, as nonprofits grow larger, have more earmarked assets, and spend more on fundraising, they are able to earn more revenue. We also find positive significant effects for donation dependence and government dependence, highlighting the importance of external sources of revenue for social services and relief organizations. Results further suggest that more concentrated revenue streams and a more diverse set of programs, on average, enable nonprofits to increase their revenue.

2.5.2 Grant Provision

Table 2.4 reports the GEE and FE estimation results of Equation (2.2). Column 1 of Table 2.4 reports the GEE estimates that are population average effects, measuring both within- and between-nonprofit effects of the variables for the full sample (Shah *et al.*, 2017). Column 2, on the other hand, reports the FE estimates that show the within-nonprofit effects for nonprofits that provided grants to other organizations in at least one year of the observation period. As expected in Hypothesis 2a, results show that higher dependence on external sources, i.e., donations and government grants, leads to a higher level of grant provision to other organizations. GEE estimates show that a one percentage point increase in donation (government) dependence, on average, leads to 6.19% (5.89%) more grants provided to other organizations (significant at $p < 0.001$). These effects are smaller in magnitude as we look at the within effects for the grant-provider subsample. As the share of an average nonprofit's income from donations (government grants) increases by one percentage point, it provides 0.51% (1.97%) more grants to other organizations.

Results also provide partial support for Hypothesis 2b. The GEE estimate of the effect of revenue growth is statistically insignificant ($p = 0.541$). However, the FE estimates show that nonprofits that provided grants in at least one year in our data, use this strategy more extensively when they observe larger increases in their revenue. Specifically, for a one percentage point increase in revenue growth, an average grant-provider nonprofit increases the amount of grants provided to other organizations by 0.15% (significant at $p < 0.001$). These results suggest that it is unlikely that a nonprofit with no history of grant provision starts using this strategy simply because

Table 2.4: Generalized estimating equation (GEE) and fixed-effects (FE) estimation results for grants. (Numbers in parentheses show robust standard deviations.)

	GEE	**FE**
Dependent variable	$Grants_{it}$	$\sinh^{-1}(Grants_{it})$
$DonationDependence_{it}$	0.0601 (0.0168) [$p < 0.001$]	0.0051 (0.0024) [p=0.032]
$GovernmentDependence_{it}$	0.0572 (0.0144) [$p < 0.001$]	0.0195 (0.0035) [$p < 0.001$]
$RevenueGrowth_{it}$	0.0004 (0.0007) [p=0.541]	0.0015 (0.0004) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0351 (0.0101) [$p < 0.001$]	0.0120 (0.0057) [p=0.037]
$\sinh^{-1}(FixedAssets_{it})$	0.1557 (0.0628) [p=0.013]	0.0310 (0.0170) [p=0.068]
$\sinh^{-1}(Earmarked_{it})$	0.0825 (0.0222) [$p < 0.001$]	0.0590 (0.0122) [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.5807 (0.0863) [$p < 0.001$]	0.0473 (0.0136) [$p < 0.001$]
$ProgramConcentration_{it}$	2.4555 (0.5509) [$p < 0.001$]	-1.7487 (0.3189) [$p < 0.001$]
$RevenueConcentration_{it}$	0.1981 (0.9394) [p=0.833]	-0.0971 (0.2790) [p=0.728]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	-0.0833 (0.0264) [p=0.002]	-0.2427 (0.0237) [$p < 0.001$]
Intercept	-5.4637 (1.3212) [$p < 0.001$]	
$Year_t$	included	included
Observations	169142	41835
χ^2 test (F test)	1301.5650 [$p < 0.001$]	19.7499 [$p < 0.001$]

GEE model uses a Gaussian distribution, a log link function, and an exchangeable correlation matrix.

of a large increase in its revenue. This can be attributed to the difficulty and costs for a nonprofit without the experience of grant provision to identify and reach out to eligible grantee organizations. Further, we note that, on average, revenue growth, absolute annual change in revenue growth, and coefficient of variation in revenue are significantly higher in the subsample of grant-provider nonprofits as compared to those that never provide any grants (at $p < 0.001$). Specifically, grant-provider nonprofits have an average revenue growth of 14.33% while this value equals 9.26% for other organizations. Similarly, the absolute one-year change in revenue growth equals 49.09% for this subsample and 34.22% for those that never use this strategy. Finally, the coefficient of variation of revenue equals 0.33 and 0.25 for these two subsamples, respectively. These suggest that nonprofits use the grant provision strategy when revenue volatility exceeds certain levels, and relatively small changes in revenue may not provide enough incentives to use this strategy.

Results reported in Table 2.4 also indicate that reserves are positively associated with grants, while there is a negative association between grants and program expenses. This suggests that, in nonprofits' budget allocation, grants play the role of a substitute to program expenses and a complement to reserves, further supporting the argument that the main incentive for the grant provision strategy is the widespread use of financial metrics that value program expenses but do not differentiate between direct program expenses and grants.

2.6 Extensions

2.6.1 High vs. Low Performers

Donors are particularly sensitive to program expenses when PSR is lower than certain thresholds. For example, donors are warned against donating to nonprofits with PSR levels lower than 65% (Taylor, 2007). Therefore the grant provision strategy can be particularly effective for nonprofits that would otherwise have low PSRs, i.e., those whose expenses on their own programs makes up a relatively small portion of their total expenses. Our findings in Section 2.5.2 also suggest that grants are used as a substitute for program expenses, i.e., nonprofits with lower levels of program spending provide more grants to other organizations. Therefore, we extend our analysis in Section 2.4.1 and perform a split-sample analysis for subsamples of nonprofits with low and high average direct PSR levels, where direct PSR is defined as the percentage of total expenses reported as program expenses excluding grants. We define nonprofits with low (high) direct PSR levels as those whose average direct PSR is lower (higher) than the median in the data (84.33).

Results, reported in Table 2.5, provide support that the grant provision strategy is more beneficial for nonprofits whose direct expenses on their core programs, on average, makes up a relatively smaller portion of their total expenses. The effect of grants on revenue is positive and significant (at $p = 0.001$) for nonprofits with average low direct PSR levels, but this effect is insignificant for other nonprofits ($p = 0.429$). Conversely, results show that maintaining higher levels of reserves is beneficial for nonprofits with average high direct PSR levels (significant at $p = 0.012$), but not for those with low direct PSRs ($p = 0.849$). These findings complement our results in Section 2.5.2 that grants and reserves can generally be viewed as complement strategies. In our data, on average, nonprofits with low direct PSR levels spend a significantly higher fraction of their budgets on grants and keep a significantly higher level of reserves. In the subsample of nonprofits with low (high) direct PSR levels, an average nonprofit allocates 8.77% (0.23%) of its total expenses to grants (significantly different at $p < 0.001$). Further, reserve levels are non-negative in 80.07% (76.96%) of the observations, and positive reserve levels make up an average of 33.57% (27.46%) of nonprofits' budgets in the low (high) direct PSR subsample. Therefore, results suggest that the benefits of grants are greater at higher levels, but reserves can only be beneficial if maintained at lower levels. These findings further support the argument that external sources do not differentiate between grants and program expenses, but can be sensitive to reserves which limit the nonprofits' reported program expenses.

2.6.2 Administrative Burden of Grants

The main inefficiency associated with the grant provision strategy is that it increases the administrative burden to make a social impact. While providing grants to other organizations allows a nonprofit to increase its program spending without having to spend the funds on its own programs, it effectively passes on the administrative burden to the recipient organizations and creates redundant administrative costs (Arya and Mittendorf, 2016). Further, larger nonprofits may have the capac-

Table 2.5: Heteroskedasticity-based instrumental variable (HBIV) estimation results for revenue for subsamples of nonprofits with low and high average direct PSR levels. (Numbers in parentheses show robust standard deviations.)

Dependent variable: $\sinh^{-1} Revenue_{it}$	Low direct PSR	High direct PSR
$\sinh^{-1}(Grants_{i(t-1)})$	0.0168 (0.0051) [p=0.001]	0.0040 (0.0050) [p=0.429]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0263 (0.0022) [$p < 0.001$]	0.2619 (0.0142) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	-0.0001 (0.0003) [p=0.849]	0.0006 (0.0002) [p=0.012]
$\sinh^{-1}(FixedAssets_{it})$	0.0100 (0.0013) [$p < 0.001$]	0.0072 (0.0012) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0042 (0.0006) [$p < 0.001$]	0.0014 (0.0005) [p=0.004]
$DonationDependence_{it}$	0.0029 (0.0002) [$p < 0.001$]	0.0025 (0.0002) [$p < 0.001$]
$GovernmentDependence_{it}$	0.0048 (0.0003) [$p < 0.001$]	0.0029 (0.0002) [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0143 (0.0008) [$p < 0.001$]	0.0082 (0.0006) [$p < 0.001$]
$ProgramConcentration_{it}$	-0.1046 (0.0188) [$p < 0.001$]	-0.0373 (0.0204) [p=0.068]
$RevenueConcentration_{it}$	0.3102 (0.0226) [$p < 0.001$]	0.1136 (0.0220) [$p < 0.001$]
$Year_t$	included	included
Observations	80965	82343
F test	164.0671 [$p < 0.001$]	204.6407 [$p < 0.001$]
Underidentification test	101.5229 [$p < 0.001$]	61.5179 [$p < 0.001$]
Hansen J test	17.2025 [p=0.2455]	10.1778 [p=0.7491]

$\sinh^{-1}(Grants_{i(t-1)})$ is treated as endogenous.

ity to spend the received grants on their missions without disrupting their existing programs. In fact, receiving grants can help these nonprofits against the unexpected downturns in their revenue and allow them to fill their expense gaps without the need to use their reserves (Calabrese, 2018). Smaller nonprofits, however, have a more limited capacity and may not be able to efficiently convert the grants received into services for beneficiaries. An example is the criticism that the Red Cross received in Haiti where it provided a significant amount of grants to small local organizations and so was criticized for creating a "cycle of overhead" and increasing redundant overhead costs (Elliott and Sullivan, 2015; Arya and Mittendorf, 2016).

Therefore, we investigate the impact of receiving grants from other organizations on nonprofits' administrative costs. The IRS requires nonprofits to report, in Schedule I of Form 990, the details of grants provided to other organizations for any recipient that received more than USD 5,000. Therefore, to measure the amounts of grants that nonprofits in our data received in each year, we used the dataset of these grant transactions during 2010–2016, created by IBM Watson's Causebot by extracting fields from schedule I of IRS Form 990. We created a new variable, *grant income*, that, in any given year of data, calculates the total amounts of grants received by the nonprofit. We also define a *grant income dummy* variable that equals one if the nonprofit has received grants from other organizations in that given year, and zero otherwise. After removing outlier observations with negative grant income, grant income higher than total revenue, grant income higher than total donations, and non-positive administrative expenses, the final dataset includes 176,002 organization-year observations of 32,167 nonprofits during 2010–2016. We estimate Equation (2.3),

$$\begin{aligned}\sinh^{-1}(AdministrativeCost_{it}) =& \sigma_1 GrantIncomeDummy_{it} \\ &+ \sigma_2 \sinh^{-1}(GrantIncome_{it}) + \sigma_2 Z_{it} \\ &+ \phi_t + v_i + mu_{it},\end{aligned} \tag{2.3}$$

where the dependent variable is the IHS of *administrative costs* and the main explanatory variables are the dummy variable indicating whether the organization received any grants and the IHS of total *grant income*. We note that the value of grants income is zero in 67% of our data. Therefore, we include the dummy variable to consider the possibility of a nonlinear relationship where the effect of interest is different at the value of zero. The set of control variables, Z_{it}, includes the following. Similar to grant income, revenue from other sources is expected to increase administrative costs given the activities required to use the funds to provide the desired services (Arya and Mittendorf, 2016). We therefore control for the nonprofits' income from *donations*, *government grants*, and *own income* by including the IHS-transformed values of these variables. Also, to capture the inter-dependencies between budget allocation decisions, as observed in Section 2.5.2, we also add the IHS of *grants* provided to other organizations, the IHS of *program expenses*, and the IHS of *fundraising expenses*. Similar to Equations (2.1) and (2.2), we also control for the IHS of nonprofits' *fixed assets*, the IHS of *reserves*, the IHS of *earmarked assets*, *program concentration* and *revenue concentration.* Note that, since we now separate grants received from other organizations from donation income, we recalculate revenue concentration as the HHI of income from the four sources of donations, grants, government grants, and own income. Finally, we also include organization fixed effects and year dummies in the model.

In addition to including a dummy variable, we also consider the potential non-linear effect of grant income on administrative costs and add a quadratic term, $\sinh^{-1}(GrantIncome_{it})^2$, to the base model in Equation (2.3). Further, to investigate whether receiving grants is more costly for smaller nonprofits, we include an interaction term between grant income and fixed assets in the full model in Equation (2.4).

$$\begin{aligned}\sinh^{-1}(AdministrativeCost_{it}) = {} & \delta_1 GrantIncomeDummy_{it} \\ & + \delta_2 \sinh^{-1}(GrantIncome_{it}) \\ & + \delta_3 \sinh^{-1}(GrantIncome_{it})^2 \\ & + \delta_4 \sinh^{-1}(GrantIncome_{it}) \times \sinh^{-1}(FixedAssets_{it}) \\ & + \delta_5 Z_{it} + \phi_t + v_i + mu_{it}, \qquad (2.4)\end{aligned}$$

Results of FE estimations of the base model, with and without the dummy variable, are reported in Table 2.6. We find that, as expected, when nonprofits receive more grants from other organizations, their administrative costs increase. Column 1 of Table 2.6 shows that a one percent increase in grant income is associated with a 0.14% increase in administrative costs (significant at $p < 0.001$). As we include the grant income dummy variable in the model, as reported in column 2 of Table 2.6, the coefficient estimate for σ_2 indicates the change in administrative costs excluding the cases where the nonprofit has no income from grants. We observe a larger effect size; a one percent increase in grant income is associated with a 0.53% increase in administrative costs. Note that this effect is larger than the effect of donations on administrative costs. Considering that nonprofits in our data, on average, receive only 2.35% of their revenue from grants and 32.28% from donations, this result shows that a certain amount of revenue from grants increases a nonprofit's administrative costs significantly more than the same amount of revenue from donations. Further, note that the effect of grant income dummy variable is negative and significant (at $p = 0.019$), suggesting a nonlinear effect. It is important to note that these grants are also sensitive to the recipient's financial metrics (Eftekhar *et al.*, 2017). It is therefore likely that nonprofits try to minimize their administrative costs to be able to receive grants from other organizations.

Table 2.6: Fixed-effects estimation results for administrative costs. (Numbers in parentheses show robust standard deviations.)

Dependent variable: $\sinh^{-1}(AdministrativeCost_{it})$		
$\sinh^{-1}(GrantIncome_{it})$	0.0014 (0.0004) [$p < 0.001$]	0.0053 (0.0017) [p=0.002]
$GrantIncomeDummy_{it}$		-0.0443 (0.0188) [p=0.019]
$\sinh^{-1}(Donations_{i(t-1)})$	0.0041 (0.0005) [$p < 0.001$]	0.0043 (0.0005) [$p < 0.001$]
$\sinh^{-1}(GovernmentGrants_{i(t-1)})$	0.0073 (0.0007) [$p < 0.001$]	0.0074 (0.0007) [$p < 0.001$]
$\sinh^{-1}(OwnIncome_{i(t-1)})$	0.0124 (0.0010) [$p < 0.001$]	0.0124 (0.0010) [$p < 0.001$]
$\sinh^{-1}(Grants_{i(t-1)})$	0.0024 (0.0008) [p=0.004]	0.0024 (0.0008) [p=0.004]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0121 (0.0047) [p=0.010]	0.0120 (0.0047) [p=0.010]
$\sinh^{-1}(Fundraising_{it})$	0.0076 (0.0010) [$p < 0.001$]	0.0076 (0.0010) [$p < 0.001$]
$\sinh^{-1}(FixedAssets_{it})$	0.0263 (0.0015) [$p < 0.001$]	0.0263 (0.0015) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0024 (0.0003) [$p < 0.001$]	0.0024 (0.0003) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0069 (0.0006) [$p < 0.001$]	0.0069 (0.0006) [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0612 (0.0223) [p=0.006]	-0.0611 (0.0223) [p=0.006]
$RevenueConcentration_{it}$	0.0579 (0.0201) [p=0.004]	0.0621 (0.0204) [p=0.002]
$Year_t$	included	included
Observations	175874	175874
F test	116.6961 [$p < 0.001$]	111.0151 [$p < 0.001$]

Table 2.7 reports FE estimation results of the full model. Results further support that the effect of grant income on administrative costs is nonlinear and convex (sig-

nificant at $p < 0.010$). Therefore, although nonprofits make efforts to appear efficient to their grantors, the administrative burden of grants become significantly higher as the amounts of grants increase. The negative coefficient estimate for the interaction between grant income and fixed assets indicates that, in terms of administrative costs, receiving grants are more costly for grantees that are smaller in size (significant at $p < 0.030$). These results are in line with our findings in Section 2.5.2 that nonprofits have a higher tendency to pass on their funds to other organizations when they experience sharp increases in their revenue. The convex increase in administrative costs indicates a plausible explanation. When nonprofits receive large amounts of grants, their administrative costs can increase significantly, which can be viewed negatively by external sources. Therefore, they may in turn decide to use the grant provision strategy to appear more efficient, creating a longer chain of overhead costs overall. Similarly, smaller nonprofits for which receiving grants is more costly, in our data, also have higher revenue volatility. The avreage coefficient of variation of revenue for nonprofits with average total expenses lower (higher) than USD 5M equals 0.29 (0.18).

2.7 Robustness Checks

We employed various robustness checks to verify our results. We used different subsamples of our data to estimate Equations (2.1) and (2.2). First, we removed nonprofits that reported zero fundraising expenses in all years of our data (Andreoni and Payne, 2011). Second, as reports of non-positive administrative expenses cast doubt over reliability of the reports, we excluded such observations (Tinkelman and Mankaney, 2007). Third, following Andreoni and Payne (2003), we excluded nonprofits which reported zero fundraising expenses but positive donation income for two consecutive years more than twice in our data, or reported zero fundraising but

Table 2.7: Fixed-effects estimation results for administrative costs. (Numbers in parentheses show robust standard deviations.)

Dependent variable: $\sinh^{-1}(AdministrativeCost_{it})$			
$\sinh^{-1}(GrantIncome_{it})$	-0.0275 (0.0127) [p=0.030]	0.0085 (0.0023) [$p < 0.001$]	-0.0274 (0.0127) [p=0.031]
$GrantIncomeDummy_{it}$	0.1354 (0.0713) [p=0.057]	-0.0547 (0.0196) [p=0.005]	0.1422 (0.0712) [p=0.046]
$\sinh^{-1}(GrantIncome_{it})^2$	0.0015 (0.0006) [p=0.009]		0.0016 (0.0006) [p=0.004]
$\sinh^{-1}(GrantIncome_{it}) \times \sinh^{-1}(FixedAssets_{it})$		-0.0002 (0.0001) [p=0.024]	-0.0002 (0.0001) [p=0.017]
$\sinh^{-1}(Donations_{i(t-1)})$	0.0043 (0.0005) [$p < 0.001$]	0.0043 (0.0005) [$p < 0.001$]	0.0044 (0.0005) [$p < 0.001$]
$\sinh^{-1}(GovernmentGrants_{i(t-1)})$	0.0074 (0.0007) [$p < 0.001$]	0.0074 (0.0007) [$p < 0.001$]	0.0074 (0.0007) [$p < 0.001$]
$\sinh^{-1}(OwnIncome_{i(t-1)})$	0.0124 (0.0010) [$p < 0.001$]	0.0125 (0.0010) [$p < 0.001$]	0.0125 (0.0010) [$p < 0.001$]
$\sinh^{-1}(Grants_{i(t-1)})$	0.0024 (0.0008) [p=0.004]	0.0024 (0.0008) [p=0.004]	0.0023 (0.0008) [p=0.004]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0120 (0.0047) [p=0.010]	0.0120 (0.0047) [p=0.010]	0.0120 (0.0047) [p=0.010]
$\sinh^{-1}(Fundraising_{it})$	0.0076 (0.0010) [$p < 0.001$]	0.0076 (0.0010) [$p < 0.001$]	0.0076 (0.0010) [$p < 0.001$]
$\sinh^{-1}(FixedAssets_{it})$	0.0263 (0.0015) [$p < 0.001$]	0.0269 (0.0015) [$p < 0.001$]	0.0269 (0.0015) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0024 (0.0003) [$p < 0.001$]	0.0024 (0.0003) [$p < 0.001$]	0.0024 (0.0003) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0069 (0.0006) [$p < 0.001$]	0.0069 (0.0006) [$p < 0.001$]	0.0069 (0.0006) [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0610 (0.0223) [p=0.006]	-0.0612 (0.0223) [p=0.006]	-0.0610 (0.0223) [p=0.006]
$RevenueConcentration_{it}$	0.0634 (0.0204) [p=0.002]	0.0670 (0.0206) [p=0.001]	0.0687 (0.0206) [p=0.001]
$Year_t$	included	included	included
Observations	175874	175874	175874
F test	111.0151 [$p < 0.001$]	112.2976 [$p < 0.001$]	107.1636 [$p < 0.001$]

positive donations in at least three consecutive years. Fourth, we follow Andreoni and Payne (2011) and re-estimate our models for subsets of data where various sub-sectors are excluded. We note that in the subsample of nonprofits that provided grants in at least one year of our data, for a large number of observations the value of grants equals zero. Therefore, we checked for robustness of our FE estimation of Equation (2.2) using a Poisson pseudo-maximum likelihood estimation which provides reliable estimates when the dependent variable takes on the value of zero in a large portion of data (Santos Silva and Tenreyro, 2006). Finally, we estimated Equation (2.3) for a subset of nonprofits that received grants in at least one year of data. Results of these tests, which support robustness of our results, are presented in Appendix G.

2.8 Concluding Remarks

Results of this paper confirm that the grant provision strategy is beneficial for nonprofits in terms of short- and long-term revenue, and in turn, can increase their long-term impact. However, these benefits come at the expense of higher administrative burden in making the social impact. Despite these costs, our results suggest that donors do not differentiate between the budget directly spent on a nonprofit's core programs and that provided to other organizations as grants. We show that this strategy is utilized more extensively by and is particularly effective for nonprofits that would otherwise appear inefficient in a sector dominantly evaluated by general financial measures. Therefore, our findings highlight the need for metrics that better capture the efficiency of nonprofits. Given that donors prefer to make a direct social impact through their contributions (Gneezy *et al.*, 2014) and prefer to have more control over the use of their donations (Aflaki and Pedraza-Martinez, 2016), it is expected that they are sensitive to the costs resulted by the grant provision strategy and therefore differentiate these expenses if they are provided with and have access to the information.

Our results also highlight the important roles of resource dependency and revenue volatility in the nonprofit sector. We find that higher dependence on external sources and higher revenue volatility are generally associated with a greater focus on the grant provision strategy. Results show smaller organizations, that generally have more volatile revenues, find receiving grants to be more costly. Further, receiving large amounts of grants considerably increases a nonprofit's administrative costs which can lead to further use of this strategy in an effort to appear more efficient. Therefore, our findings suggest that, in their grant provision decisions, nonprofits should consider their grantees and how they will be influenced by these grants. If the grantees have higher operational capacities and expect the grants ahead of time and can plan for an efficient use of the grants, the excessive administrative costs can be avoided.

This study has limitations that provide avenues for future research. We show that grant provision leads to more revenue and, in turn, more program expenses in the long term, thus potentially increasing the social impact. On the other hand, our results indicate the administrative costs associated with this strategy. However, we are not able to evaluate the overall impact of this strategy on the sector. First, our dataset is not comprehensive and therefore we are not able to track all of the grant transactions. For instance, we do not observe small grantees that are not required to file Form 990 (and instead file a shorter version). Second, to address this question, more detailed information regarding nonprofits' performance and social impact is needed. We further note that concerns of endogeneity and unavailability of valid external IVs limited our ability in investigating the impact of grant provision in interaction with other factors. Future research can study circumstances under which grant provision is more or less beneficial for nonprofits.

Chapter 3

FORMING A COALITION WHEN TIME IS SHORT: HORIZONTAL COORDINATION IN DISASTER RELIEF OPERATIONS

Abstract

Despite the pressing need for harmonized relief operations and initiatives such as the UN cluster mechanism, lack of effective coordinated response remains a problem. In this paper, we develop a non-cooperative game theoretical model to analyze horizontal coordination among non-governmental organizations in a sudden-onset disaster relief operations in centralized and decentralized models. We find that coordination does not always maximize social welfare. Further, our analysis indicates that time inefficiencies due to bureaucracies involved in coordination mechanisms are substantial obstacles against higher levels of coordination, especially in urgent response operations. We also show that decentralization of coordination mechanisms increases both the coordination level and social welfare. We show that a decentralized model is particularly effective when urgency is high and coordination involves considerable bureaucracy.

3.1 Introduction

The concurrence of sharply growing demand for humanitarian actions and shrinking resources available to humanitarian organizations (HOs) (Development Initiatives, 2020) necessitates coordination among HOs to improve the performance of relief systems (Holguín-Veras *et al.*, 2012; Ergun *et al.*, 2014). Due to the pressing need for harmonized relief operations, the United Nations (UN) put significant effort into facilitating coordination and building partnerships among HOs through initiating the cluster mechanism in 2005, and later calling for stronger global partnerships in its 17th Sustainable Development Goal (United Nations, 2016). Despite these efforts, lack of effective coordinated response remains a challenge (Ruesch *et al.*, 2021). A recent example is the response to Ebola outbreak where ineffective coordination led to an impotent initial response (McInnes, 2015).

While through coordination, HOs are able to enhance resource utilization, which leads to benefits that are not achievable by individual organizations (Ergun *et al.*, 2014), the desired performance is only achieved through an effective well-designed coordination model. A large HO executive indicated to us "*Bad coordination can be more damaging than no coordination.*" For example, bureaucratic coordination and time-consuming meetings, typically led by large international HOs, which may even end up with no concrete decisions (Knox Clarke, 2013; Pillai *et al.*, 2014; Olu *et al.*, 2016) only discourage smaller HOs whose limited resources exclude them from participating in coordination efforts (Knox Clarke and Campbell, 2015). Moreover, participation of smaller local HOs has always remained marginal (Binder and Grünewald, 2010; Steets *et al.*, 2010), while their involvement is key in the success of prompt response operations (Vinbury, 2017). In Ebola response operations, for example, absence of such actors who had local knowledge and expertise resulted in sub-optimal decisions and unsuccessful coordination (DuBois *et al.*, 2015).

In this paper, we center our analysis on horizontal coordination among non-governmental organizations involved in a sudden-onset disaster relief operations. Horizontal coordination refers to the operational alignment among a group of entities serving the same market (Ergun *et al.*, 2014; Simatupang *et al.*, 2002; Eftekhar *et al.*, 2017). While in most relief operations, HOs maintain their autonomy and no single organization exerts authority over the others, the structure of the coordination mechanisms can be centralized or decentralized (Dolinskaya *et al.*, 2011). In a centralized model, all of the participating organizations join a single coalition, while in a decentralized model, organizations form smaller groups that are loosely connected. In this paper, we consider both structures.

We develop a general utility function based on the existing literature and interviews with many executives at several HOs. The utility function includes two critical components; an HO's expected donation income through contributing to relief operations, and their operational performance during the relief operations. To model an organization's expected income, we consider public donations that are affected by an HO's media exposure and their reputation, and grants from governments and institutions that is affected by an HO's performance. We consider demand coverage and timeliness of response as an HO's operations performance. Next, we develop a sequential non-cooperative game theoretical setting to model HOs' coordination decisions. We consider two types of players, small and large HOs, and analyze their optimal (rational) decisions when they are myopic vs. forward looking. We then compare these decisions with those that would maximize social welfare.

We find that coordination does not always maximize social welfare. Our analysis indicates that time inefficiencies due to bureaucracies involved in joining a coalition is a substantial factor that prevents higher levels of coordination. As a result, in urgent disasters, especially if coordination is time inefficient and bureaucratic, the assumption that HOs should reach to the maximum level of coordination is not valid. Indeed, underestimating the time costs of coordination may lead to coalitions larger (in terms of number of contributing HOs) than optimal. We find that the negative impact of time cost on smaller HOs whose capacity is limited is more severe, and so if they anticipate a large number of HOs will contribute into a coalition, they should rationally choose not to involve. Aligned with these observations are the cases in recent years. For instance, in Haiti, while the major HOs were still engaging in coordinated decision-making process instead of quick action, some small HOs were already delivering supplies in the field (Bolton, 2011).

Generally, a wide range of HOs with different cultures and structures are involved in a disaster relief operations, and such differences create additional barriers to coordination and impair coordination performance (Van Wassenhove, 2006; Knox Clarke and Campbell, 2015). However, we note that overtly centralized systems (where all participating HOs must join one coalition) have shown inefficiency in some response operations (Olu *et al.*, 2016). For instance, in the UN cluster systems, large international and small local HOs are pooled into a cluster and are all expected to join the same table, where smaller local HOs may not see a place for themselves (Vinbury, 2017). Challenges in communication and translation are among the obstacles that contribute to this exclusion (Moore *et al.*, 2003). There have also been efforts and examples towards more decentralized approaches, such as the Ebola response operations over time (DuBois *et al.*, 2015), or how the Logistics Cluster operates. Nevertheless, a new decentralized approach is suggested by the Inter-Agency Standing Committee (IASC) that emphasizes on formation of small task-oriented Technical Working Groups (TWGs) in clusters on a needs-basis. In practice, these TWGs are time limited and dissolved after a specific task is done (IASC, 2015). In the Haiti response operations, among the 11 different clusters that were activated, only the protection cluster included two separate sub-clusters (Vinbury, 2017). In this paper, we further analyze this model, and investigate how the level of decentralization affects the coordination level and social welfare. We consider decentralization as separating different types of HOs, specifically small local and large international HOs, into communicating sub-coalitions. We find that decentralization of coordination mechanisms increases both the coordination level and social welfare, as it reduces the time inefficiencies by removing barriers to coordination. This model is particularly effective during urgent response operations and when coordination involves considerable bureaucracy.

3.2 Literature Review

The literature on coordination between HOs is mostly limited to conceptual, case study research, and surveys (Moshtari and Gonçalves, 2017). Researchers have investigated drivers of and impediments to coordination among HOs (Balcik *et al.*, 2010; Dolinskaya *et al.*, 2011; Eftekhar *et al.*, 2017); Balcik *et al.* (2010) provide an overview of coordination in relief operations and discuss the main barriers to coordination such as diversity of actors and competition over funding and media attention. Similarly, Dolinskaya *et al.* (2011) indicate that diversity of HOs involved in disaster relief and the urgency of relief operations are the main challenges in coordination between HOs. Eftekhar *et al.* (2017) show that the lack of horizontal coordination among HOs is intensified by their competition to receive more media exposure. Researchers have also considered the role of inter-organizational factors such as differences in organizational cultures and structures (Van Wassenhove, 2006; Schulz and Blecken, 2010), compatibility and resource complementarity (Moshtari, 2016), and symmetry between parties, such as size disparity (McLachlin and Larson, 2011; Knox Clarke and Campbell, 2015).

A limited number of studies have attempted to evaluate the existing mechanisms such as the cluster mechanism, though through qualitative methods. For example, Steets *et al.* (2010) report six case studies of the implementation of the cluster mechanism (at country level) and provide recommendations such as increasing the focus on the local level. Steets *et al.* (2014) provide an evaluation of food security cluster and underline the constraints to effective coordination, including the need to involve local actors. Using surveys and interviews, Knox Clarke and Campbell (2015) explore humanitarian clusters and find that the relationships between HOs are rather loose where each HO works independently while using the shared information to align its activities with other members. Jahre and Jensen (2010) present a conceptual framework on the trade-offs and challenges in intra- and inter-cluster coordination based on a case study of the logistics cluster. Nevertheless, most studies focus on coordination models in specific functions or concentrate on a specific aspect of coordination. For instance, Bagchi *et al.* (2011) consider auction mechanisms that allow coordination between suppliers and carriers in humanitarian food aid procurement. Altay and Pal (2014) study information sharing in the cluster mechanism using agent-based simulation, and analyze the role of cluster leads. Finally, Ruesch *et al.* (2021) also focus on the role of cluster leads using qualitative and simulation-based approaches and reveal that the dual role of cluster leads in facilitating coordination while also investing in their own operations contributes to low levels of coordination in clusters.

The number of studies that propose game theoretical models to investigate coordination between HOs is very limited. Coles and Zhuang (2011) study the problem of optimal resource allocation of different types of actors in response to a major disaster. A non-cooperative game model is utilized to study partner selection in a disaster relief environment when the partners might be incompatible, e.g., in terms of organizational cultures. The players' goal is to maximize the efficacy of their response where efficacy increases by coordination through reducing duplication of efforts and increasing resource utilization. Toyasaki *et al.* (2017) use a newsvendor model in a non-cooperative setting to analyze horizontal coordination between HOs in terms of exchanging stock through the United Nations Humanitarian Response Depot (UNHRD) network. Ergun *et al.* (2014) investigate the optimal allocation of cost and benefit of coordination when an initial investment for information technology tools is required. They use a cooperative game framework to consider different cooperative cost-allocation schemes imposed to a coordination mechanism.

This paper contributes to the extant literature in several ways. First, there exists only a few analytical studies that focus on coordination in a specific function such as inventory exchanging (Toyasaki *et al.*, 2017), or a specific aspect of coordination such as improving resource utilization (Coles and Zhuang, 2011; Ergun *et al.*, 2014). In order to further expand our understanding, this paper proposes a holistic view by considering the interplay between various influencing factors that have not been considered in a single frame; Our proposed model takes an HO's resource utilization, response time, incentives to collect public donations, and earning grants into account. These factors are selected through collaboration (and interview) with many experienced practitioners as well as the existing literature. Second, while the literature offers valuable insights regarding the drivers and impediments to coordination, it is limited to HOs' coordination decisions assuming that coordination is beneficial for all parties and increases the total social welfare. In this paper, we analyze the value of coordination from different perspectives, and demonstrate that higher levels of coordination do not necessarily lead to higher social welfare. Finally, we illustrate that the structure of coordination mechanism plays a critical role to incentivize the participation of smaller HOs, and suggest a new clustering approach to further increase the participation of these organizations.

3.3 Model Settings

Our model focuses on the immediate response operations after a large-scale sudden-onset disaster, where multiple HOs (players) with determined capacities participate in relief efforts. An organization's capacity is defined as their ability to satisfy demand including, e.g., shipping inventory to the field, having financial capacity to procure after disaster, and owning sufficient human resources to conduct logistics. International HOs only involve in a disaster relief operations when demand exceeds the available capacity of local HOs and the domestic government. Therefore, we assume that the total demand is larger than the capacity of the HOs. Focusing on immediate relief period (i.e., short-term post-disaster), the first question to address is whether an HO joins a coalition. We consider two types of players, small and large HOs. There is no official sequence for HOs to join a coalition. However, as we were told by many practitioners, in practice, there is a sequence for organizations to join the coalition. This sequential form is somehow organic; large HOs often have a history of partnership or may already be working together before the disaster occurs, and their managers know each other. Small/local HOs, however, are usually next in line and, for instance, it is recommended that clusters actively reach out to them to invite them join the coalition (Binder and Grünewald, 2010). We, therefore, develop the model as a sequential game. Given the sequence, we consider two types of decision making: myopic and forward-looking. A myopic player considers decisions made by the preceding players in the sequence and disregards those that might join next, while a forward-looking player anticipates the decisions of next players and takes that into account. We consider the problem from two perspectives: HOs' utility and social welfare. Therefore, we first analyze coordination decision made by an organization assuming that the goal of each HO is to maximize its own utility. Next, from the social welfare perspective, we consider a central planner whose goal is to maximize social welfare.

3.3.1 Utility Function

At a high level, an HO's utility is a combination of the service it provides and its income (Steinberg, 1986). In the context of our study, service is translated to minimizing deprivation, and so performance is evaluated in terms of the number of affected people served (i.e., *demand coverage*) and the response time in provision of this service (i.e., *timeliness*). As for income, we consider HOs' two main sources of income, *donations* from the general public and *grants* received from governments and large institutions. Next, we provide an overview of these four elements.

Demand Coverage

A commonly cited goal of HOs during disaster response is maximizing coverage that could be achieved through coordination (Ergun *et al.*, 2014). Coordination provides HOs with a platform to effectively communicate, share information, agree on joint policies, and harmonize their activities to enhance their performance. One of the authors (who has been serving international HOs for many years) has seen many examples where two HOs that do not coordinate target the same families with the same item, and so each family will receive the item twice. Therefore, these organizations distribute their limited resources among fewer number of people.

Timeliness

Time pressure is a key aspect in relief operations, especially in the aftermath of a large scale sudden-onset disaster (Altay and Labonte, 2014), and so timeliness is a key factor to achieve success. Yet, it is time consuming for coordinating HOs to collect, prepare, and share information (Knox Clarke and Campbell, 2015). Further, coordination generally comes at the expense of higher bureaucracy (Balcik *et al.*, 2010). Slow decision-making processes, sometimes even without concrete decisions (Pillai *et al.*, 2014; Olu *et al.*, 2016), that slow down response operations is considered as one of the biggest challenges of coordination among HOs (Knox Clarke and Campbell, 2015). Haiti is an example, where decision making processes hindered major HOs from taking timely action (Miller *et al.*, 2018). Similarly, in Sierra Leone Ebola response, bureaucratic processes led to slow resource mobilization (Olu *et al.*, 2016).

Donations

Research shows that HOs' donation income is influenced by their reputation (Eftekhar *et al.*, 2017; Khanna *et al.*, 1995; Steinberg, 1986) that itself is significantly associated with the media exposure that the organizations receive over time (Eftekhar *et al.*, 2017). The important role of media has been highlighted in the literature (e.g., Thévenaz and Resodihardjo (2010); Balcik *et al.* (2010); Polman (2011); Turrini *et al.* (2020)); charitable giving to relief organizations increases as the media pays more attention to a disaster (Brown and Minty, 2008). Therefore, competition over media exposure tends to be an obstacle to coordination (Balcik *et al.*, 2010; Eftekhar *et al.*, 2017). For instance, reports have associated competition between HOs over media exposure with failures in Haiti response (Waterfield, 2010). When multiple HOs are involved in response operations, the media exposure might get divided among them. As a result, some HOs prefer to work individually to solely receive the attention from the media. On the other hand, in certain cases, coordination among HOs might boost the media attention that the disaster and individual HOs receive. Furthermore, an HO can avoid being singled out by other HOs or media outlets as a "not-collaborative organization." Although we are not aware of any systematic study that proves media increases coordination between HOs, an HO executive indicated to us that, despite the impediments, HOs may still decide to coordinate to *gain media visibility* and to avoid negative publicity.

Grants

Public donors are limited in their ability to assess HOs' performance in the field, and rely on secondary sources of information (such as media) and proxy measures that may not reflect HOs' actual performance. Nevertheless, institutional donors are able to inspect HOs' performance more closely and accurately (Balsam and Harris, 2014) and so, award grants to HOs considering their performance (Eftekhar *et al.*, 2017). Accordingly, assuming that coordination with other HOs improves the performance of a relief system, large donors encourage HOs to work with their peers, and participating in a coalition is considered an advantage to win grants (Schulz and Blecken, 2010).

3.4 General Centralized Model

We first consider the general form of the centralized model where there are n HOs deciding whether to join a centralized coalition in which all participants are pooled into one group. Index i indicates position of the HO in the sequence, i.e., HO i decides whether to join after players 1 to $i-1$ have made their decisions. Coordination decision is binary (i.e., HO i decides whether to join the coalition ($x_i = 1$), or not, ($x_i = 0$)). Let $\mathbf{x}_{-i} = \{x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n\}$ denote the vector of coordination decisions by organizations other than i, where x_j indicates the known decision of player j when $j \leq i$ and the anticipated decision of player j when $j > i$. We define $N(\mathbf{x}_{-i})$ as the number of players in the coalition excluding player i, i.e., $N(\mathbf{x}_{-i}) = \sum_{j \neq i} x_j$.

Previous studies suggest that nonlinear increasing functions best fit the human suffering resulted by deprivation from goods and services over time (Wang *et al.*, 2017; Holguin-Veras *et al.*, 2013). Wang *et al.* (2017) note that, for short times after disasters, different functional forms, such as logistic growth and convex forms, are almost the same. Therefore, we penalize the timeliness of response in a convex form using an exponential function and formulate the deprivation cost resulted by timeliness of response as e^{bT} where T is the total response time. As discussed earlier, joining the coalition incurs an additional bureaucracy time. Addition of players to the coalition increases the level of bureaucracy involved in decision making and so delays the response time. However, a coalition size does not linearly increase response tardiness (Knox Clarke and Campbell, 2015). Put differently, the additional bureaucracy time is concave in the number of players involved and, we assume it has a natural logarithmic form. Thus, the total response time for player i equals $T + t_B \ln(1 + x_i N(\mathbf{x}_{-i}))$, where T represents the short-term post-disaster relief period. [1] In other words, T is the baseline response time during which each HO can deliver its capacity if it works alone. Therefore, the HO's disutility related to deprivation cost from joining a coalition of size $N(\mathbf{x}_{-i})$ is $e^{b(T+t_B \ln(1+N(\mathbf{x}_{-i})))} - e^{bT} = e^{bT}((1 + N(\mathbf{x}_{-i}))^{bt_B} - 1)$.

As more players join the coalition, each member learns more about the field conditions, the demand, and available supplies (Balcik *et al.*, 2010; McLachlin and Larson, 2011) that enable HOs to learn about the areas covered by other HOs, thereby they avoid duplication and increase their resource utilization. An HO's better performance increases their chances to receive grants (from large donors). Yet, when there is competition over media attention, joining a larger coalition means sharing the spotlight with a greater number of competitors and so less income from individuals' donations. But if media attention is synergistic, as more HOs join the coalition, they attract more attention from the media. Overall, the change in HO i's utility from joining the coalition relative to not joining is $U_i(\mathbf{x}_{-i})$ where

$$U_i(\mathbf{x}_{-i}) = \alpha_i N(\mathbf{x}_{-i}) - [1 + N(\mathbf{x}_{-i})]^{\beta} + 1, \qquad \forall i = 1, \ldots, n \tag{3.1}$$

[1] This period is typically short but critical in disaster response (United Nations Office for the Coordination of Humanitarian Affairs, 2013; Gralla *et al.*, 2014).

where $\beta = bt_B$ represents the time burden of coordination and $\alpha_i = \dfrac{\alpha_{Ci} + \alpha_{Gi} + \alpha_{Di}}{\alpha_T} > 0$ is the marginal benefits of coordination for player i.

The relative importance of deprivation cost due to timeliness of response is captured by $\alpha_T = e^{bT}$. Since the cost function has a convex form, the baseline response time changes the marginal costs of joining the coalition. Therefore, deprivation cost plays a bigger role in the utility function when the response operations are slower, e.g., when the affected area is more difficult to access.

The relative importance of demand coverage is represented by $\alpha_{Ci} = w_{Ci}\gamma c_i$, where w_{Ci} and c_i indicate the weight of demand coverage in HO i's utility and its capacity, respectively. Aligned with Ergun *et al.* (2014), we assume that, in a coordinated response, operations are divided into n geographical regions or functions and each HO is responsible for a determined function or region. If an HO decides not to join the coalition and thus has no information about the other players, their operations may overlap, leading to duplication in the relief system and waste of resources. In our model, γ represents the increase in resource utilization per coalition member where $\gamma n < 1$.

To model the role of income incentives on an HO's coordination decision, we consider that different HOs put different weights on the income earned from grants vs. public donations. The relative importance of grants in HO i's utility equals $\alpha_{Gi} = w_{Gi}\gamma c_i$, where w_{Gi} represents the weight that HO i puts on their income from grants. Given that grants are sensitive to performance, when an HO depends more on grants, resource utilization, γc_i, gains more weight in its utility function. Further, $\alpha_{Di} = w_{Di} M\theta c_i$ represents the relative importance of public donations in HO i's utility. w_{Di} indicates the weight that the HO considers for public donations. Media coverage for some disasters is more extensive than the others; The type of disaster and the location that it hits matter to how newsworthy networks find it to be. For example, Eisensee and Strömberg (2007) show that on average, it takes 38,920 deaths for a "food shortage crisis" to receive media coverage, while major networks cover news of a volcano if it leads to one death. They also estimate that "45 times as many people would have to die in an African disaster for it to garner the same media attention as a European one" (Eisensee and Strömberg, 2007). To capture media attention, we use M indicating the total coverage that the disaster receives. We further assume that larger HOs attract more media attention, as seen in practice and noted in our interviews. Depending on the media competition level, $-1 \leq \theta \leq 1$, coordination increases or decreases the media attention an HO receives during the response. The competition or synergies increase as more HOs join the coalition. When θ is negative, media attention to coordinating HOs is competitive (i.e., coordinating with other HOs results in lower media attention), while if θ is positive, media attention is synergistic (i.e., coordinating with other HOs results in higher media attention). Consequently, depending on θ, the expected donation income could be an incentive or disincentive to coordination.

In summary, the change in HO i's utility from joining a coalition of size $N(\mathbf{x}_{-i})$ derive from four fundamental elements. As illustrated in Figure 3.1, utility increases due to improved demand coverage and grant income, and utility decreases due to increased bureaucracy that manifests in slower response time. Depending on the setting, public donation income may increase or decrease.

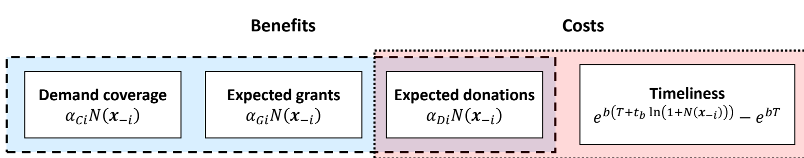

Figure 3.1: Components of the utility function.

3.4.1 Social Welfare

The central planner seeks to maximize total social welfare, defined as the summation of the utilities of all HOs involved in the operations. The society also benefits from higher demand coverage, timeliness of response, and HOs' sustainability to provide further assistance to the society in the future. Thus, social welfare, $\hat{U}(\mathbf{x})$, increases in higher demand coverage, faster response, and HOs' total income. Equation (3.2) shows social welfare, where u_0 is the total social welfare if HOs do not coordinate (i.e., $\mathbf{x} = 0$).

$$\hat{U}(\mathbf{x}) = u_0 + \sum_{j=1}^{n} x_j U_j(\mathbf{x}_{-j}) \tag{3.2}$$

Table 3.1: Notations

Indices	
i, j	Player (HO), stage in sequence, $i, j \in \{1, \cdots, n\}$
k	Player type, $k \in \{1, 2\}$
Decision variables	
x_i	Player i's decision to join the coalition ($x_i \in \{0, 1\}$)
Parameters	
α_i	Marginal benefits of coordination for player i
β	Time burden of coordination
γ	Waste factor (% of resources wasted due to lack of coordination per potential partner, $0 \leq \gamma n \leq 1$)
θ	Media competition level ($-1 \leq \theta \leq 1$)
ρ	Centralization level ($0 < \rho \leq 1$)
b	Exponential deprivation parameter
c_i	Player i's capacity in the relief efforts
M	Media coverage level of the response
T	Baseline response time
t_B	Unit bureaucracy time increase by joining the coalition
u_0	Social welfare if HOs do not coordinate
$U_i(\mathbf{x}_{-i})$	The change in utility of HO i by joining the coalition
$\hat{U}(\mathbf{x})$	Social welfare given decision vector $\mathbf{x}$
w_{Ci}	Weight of demand coverage in HO i's utility function
w_{Di}	Weight of public donation income in HO i's utility function
w_{Gi}	Weight of grants income in HO i's utility function
x^o	Social optimal solution
x^*	Equilibrium solution
y^o	Social optimal cluster size
y^*	Equilibrium cluster size

3.4.2 Comparative Statics

Benefits of Coordination:

Marginal benefits of coordination for HO i equals $\alpha_i = [(w_{Ci}+w_{Gi})\gamma + w_{Di}M\theta]c_i e^{-bT}$. Thus, marginal benefits are increasing in the waste factor, γ, which increases the impact of coordination on resource utilization. This increase is higher when the weights of demand coverage and income from grants (i.e., w_{Ci} and w_{Gi}) are greater. When media attention is synergistic (competitive), i.e., $\theta > 0$ ($\theta < 0$), marginal benefits of coordination are higher for disasters with greater (smaller) media coverage, M. Larger HOs owning higher capacity obtain higher marginal benefits of coordination and are more sensitive to changes in the aforementioned parameters. Finally, from (3.1), the total benefits of coordination for each HO, $\alpha_i N(\mathbf{x}_{-i})$, is linearly proportional to the number of HOs in the coalition.

Costs of Coordination:

Marginal costs of coordination increase as β, the time burden of coordination, increases. This factor increases when deprivation parameter, b, is high that is when urgency is high and delays in delivering the services results in high levels of deprivation (e.g., medical relief after a disease outbreak). The level of bureaucracy in coordination, t_b, is the other critical parameter; When coordination is time consuming and involves a high level of bureaucracy (e.g., when there are multiple small and large HOs with differences in language, culture, and interests), coordination time burden increases. This increase in marginal costs changes exponentially as the coalition size increases. From (3.1), we have

$$\frac{\partial U_i(\mathbf{x}_{-i})}{\partial \beta} = -\ln(1 + N(\mathbf{x}_{-i}))(1 + N(\mathbf{x}_{-i}))^{\beta} < 0,$$

showing that if $\beta > 1$, marginal change in the coordination time burden significantly increases HOs' coordination costs, especially in larger coalitions. However, if urgency is low or the system is time efficient (i.e., $\beta < 1$, so that the addition of new members does not incur a large time cost), coordination decisions are less sensitive to the exact value of β. In practice, during the short period post-disaster, HOs barely know the exact value of t_B, and so rely on their intuitive estimate of this factor; If they find the coordination system to be time efficient, they are more willing to take the risk of having underestimated the time cost. But, if they perceive the system to be inefficient, they are sensitive to the time cost since a small increase in the level of bureaucracy leads to a large change in their costs.

3.4.3 Coordination Decisions

In order to investigate HOs' coordination decisions, we first analyze the conditions under which a player would join a coalition of a specific size. From (3.1) we have $\frac{\partial U_i(\mathbf{x}_{-i})}{\partial N(\mathbf{x}_{-i})} = \alpha_i - \beta(1 + N(\mathbf{x}_{-i}))^{\beta-1}$ indicating that while the benefits of coordination, α_i, are linearly increasing in the coalition size, the costs, $\beta(1+N(\mathbf{x}_{-i}))^{\beta-1}$, increase in a convex form when $\beta > 1$. Consequently, as the coalition grows larger, the costs may outweigh the benefits at some point, making the next HOs reluctant to join. However, if $\beta < 1$, the cost increase is concave in coalition size, making large coalitions more appealing. More specifically, we have the following:

Theorem 1 *Player i joins to form a coalition of y players if $\alpha_i > \frac{y^\beta - 1}{y - 1}$.* (Proofs are provided in the Appendix.)

The threshold function is increasing in y, if $\beta > 1$, and decreasing otherwise. In other words, if deprivation resulted by the time spent in bureaucratic coordination processes is high, the minimum marginal benefits of coordination that makes it beneficial for an HO to join the coalition increases as more HOs join. On the contrary, when coordination time burden is low, HOs would be willing to join larger coalitions at smaller values for marginal benefits of coordination. Given this change in behavior, in what follows, we investigate the problem for the two scenarios where coordination time burden is high ($\beta > 1$) and low ($\beta < 1$), from the perspectives of a central planner as well as small and large HOs that are either myopic or forward looking.

3.5 Centralized Model: Large and Small HOs

We now assume that there are two types of HOs: HOs 1 through n_1 are of type 1 and have a marginal benefit parameter equal to α_1 and HOs n_1+1 through $n_1+n_2 = n$ are of type 2 with a marginal benefit parameter equal to α_2.

3.5.1 Equilibrium

The gain in utility of the yth HO of type k from joining the coalition, given that y–1 HOs are in the coalition, is denoted as $g_k(y)$. From (3.1) we have

$$g_k(y) = \alpha_k y - y^\beta - \alpha_k + 1 \qquad\qquad \forall k = 1, 2.$$

When decision making is myopic, type 1 HOs make their decisions first. The y_1th HO joins the coalition of $y_1 - 1$ HOs only if $g_1(y_1) \geq 0$. Therefore, a total of y_1^* type 1 HOs join the coalition such that

$$y_1^* = \max\{y : \alpha_1 y - y^\beta - \alpha_1 + 1 \geq 0\}.$$

Type 2 HOs are next in the sequence and make their decisions knowing that y_1^* HOs are in the coalition. Therefore, a number equal to y_2^* join, making an equilibrium coalition of size $y^* = y_1^* + y_2^*$ such that

$$y_2^* = y_2^*(y_1^*) = \max\{y_2 : \alpha_2(y_1^* + y_2) - (y_1^* + y_2)^\beta - \alpha_2 + 1 \geq 0\}.$$

When players are forward looking, $y^* = y_1^*(y_2^*) + y_2^*(y_1^*)$ players will form a coalition such that

$$\begin{cases} y_1^*(y_2^*) = & \max\{y_1 : \alpha_1(y_1 + y_2^*) - (y_1 + y_2^*)^\beta - \alpha_1 + 1 \geq 0\} \\ y_2^*(y_1^*) = & \max\{y_2 : \alpha_2(y_1^* + y_2) - (y_1^* + y_2)^\beta - \alpha_2 + 1 \geq 0\}. \end{cases}$$

3.5.2 Social Optimal

The total social welfare resulted from a coalition of y_1 HOs of type 1 and y_2 HOs of type 2 equals

$$\begin{aligned} \hat{U}(y_1, y_2) &= u_0 + y_1 g(y_1 + y_2|\alpha_1) + y_2 g(y_1 + y_2|\alpha_2) \\ &= u_0 + (y_1 + y_2)(\alpha_1 y_1 + \alpha_2 y_2 - (y_1 + y_2)^\beta + 1) - \alpha_1 y_1 - \alpha_2 y_2. \end{aligned}$$

Ignoring the integer requirement and the constraints $y_k \leq n_k$, $\forall k = 1, 2$, the central planner seeks to solve the problem

$$\max_{y_1, y_2 \geq 1} \hat{U}(y_1, y_2).$$

Thus, the social optimal coalition includes y_1^o HOs of type 1 and y_2^o HOs of type 2 where

$$(y_1^o(y_2^o), y_2^o(y_1^o)) = \arg\max_{y_1, y_2 \geq 1} \hat{U}(y_1, y_2).$$

3.5.3 Low Time Burden ($\beta < 1$)

When coordination time burden is low (i.e. $\beta < 1$), from (3.1), the increase in deprivation cost is concave in coalition size. The benefits, on the other hand, increase linearly. Therefore, joining a larger coalition is more attractive than a smaller one, leading to higher utility for all players and, thus, higher social welfare. More specifically, we find the following.

Proposition 1 *When $\beta < 1$ and HOs are myopic, a sequence in which large HOs are first leads to an equilibrium coalition that is at least as large as the equilibrium coalition resulted by the opposite sequence.*

Results show when coordination time burden is low (and so HOs are not concerned about spending time in coordination), small HOs are more willing to join if there are large HOs in the coalition. Participation of large HOs ensures benefits in terms of higher resource utilization and, if $\theta > 0$, more income. However, the additional time costs are relatively small due to the efficiency of the mechanism and/or low urgency of the operations. In contrast, if large HOs are excluded from the coalition and small HOs consider coordination only among themselves, time costs of coordination outweigh the benefits unless there are a large number of small HOs in the coalition.

Proposition 2 *When $\beta < 1$, the social optimal coalition is at least as large as the equilibrium coalition, i.e., $y^o \geq y^*$.*

This finding is in line with the assumption that HOs should aim for maximum coordination in situations where urgency is low and/or the coordination mechanism is time efficient. Under these circumstances, even though small HOs are more willing to join a coalition where large HOs are present (Proposition 1), their participation may still be less than optimal. We note that this outcome is not necessarily due to myopic decision making. It is possible that small HOs refrain from joining the coalition to avoid the costs while their addition to the coalition allows large HOs to improve their performance such that the total social welfare increases. In other words, it may be optimal that small HOs' utility and performance declines by joining the coalition while the information they provide to large HOs enhances the overall performance of the system.

3.5.4 High Time Burden ($\beta > 1$)

Proposition 3 *When $\beta > 1$, type k HOs do not join a coalition and the social optimal solution does not include type k HOs when $\alpha_k < 2^{\beta} - 1$.*

Results show that when urgency is high and the mechanism is highly bureaucratic, HOs prefer to operate alone unless marginal benefit of coordination is significantly high. In other words, only those HOs coordinate that find a large potential for increasing resource utilization (e.g., to avoid overlap of operations) and/or media attention. Note that increases in β exponentially increase the minimum threshold for α_k which makes a coalition preferable to operating alone. Put differently, higher coordination time burden makes coordination an exponentially less attractive option both from the HOs' and a central planner's perspective. Also recall that small HOs have a lower marginal utility of coordination. Therefore, high bureaucracy in the coordination mechanism especially discourages small HOs from coordination.

Proposition 4 *When $\beta > 1$ and players are myopic, a sequence where large HOs are first leads to an equilibrium coalition that has fewer (more) or an equal number of small (large) HOs as compared to the opposite sequence.*

This finding underlines small HOs' reluctance to coordinate with large HOs in urgent situations and when the mechanism is highly bureaucratic. Myopic HOs only consider the size of the coalition at the present stage. Therefore, when small (large) HOs are first in the sequence, they do not anticipate the additional coordination time needed to coordinate with large (small) HOs and, hence, underestimate the total costs. Forward looking HOs, however, acknowledge that large HOs have higher marginal benefits of coordination. Therefore, participation of large HOs is prioritized, and the resulting coalition is similar to when HOs are myopic and large HOs are first in the sequence. As previously noted, in practice, large HOs generally precede small HOs in joining coalitions. Therefore, small HOs, either myopic or forward looking, decrease their participation levels to avoid the high time burden of coordination with large HOs.

Proposition 5 *When $\beta > 1$, the equilibrium coalition is at least as large as the social optimal coalition, i.e., $y^* \geq y^o$.*

This result is against the assumption that HOs should aim for maximum coordination in situations where urgency is high and/or the coordination mechanism is time inefficient and bureaucratic. Under these situations (i.e., when $\beta > 1$), from (3.1) and (3.2), the coalition size increases the cost of coordination (for HOs and social welfare) in a convex form, while the benefits increase linearly. As a result, one HO's decision to join the coalition has a significant impact not only on its own costs, but also on all of the other participants' utilities. However, each HO, either myopic or forward looking, only considers its own costs and neglects the collective increase in all participants' response time which could lead to a lower social welfare. Therefore, HOs may underestimate the costs and form a coalition that is larger than optimal.

3.6 Decentralized Model

We now investigate the role of decentralization in the coordination mechanism. We consider the model where different types of HOs, more specifically small local and large international HOs, form separate communicating sub-coalitions. Such decentralization can help the mechanism to overcome many obstacles that exist in coordination between these two types of HOs. For instance, one of the main challenges that small local HOs face in coordinating with large HOs is language since coordination meetings are mostly conducted in English or French (Steets *et al.*, 2010; Bolton, 2011). The language also tends to be heavy with jargon that small local HOs are not familiar with (Steets *et al.*, 2010; Knox Clarke and Campbell, 2015). Therefore, when there are multiple small local and large international HOs at the same table, a considerable time is spent on translation and interpretation. It is very time consuming for small HOs to process the information that multiple large HOs share. For instance, in Pakistan, the cluster mechanism aimed to be more inclusive by sharing information, such as meeting agendas, prior to coordination meetings. However, capacity and resource limitations of small HOs prevented them from utilizing the information efficiently and being active in coordination (Knox Clarke and Campbell, 2015). In a decentralized model, the information in each sub-coalition can be aggregated and then translated and presented to the other sub-coalition, hence reducing such inefficiencies. Small HOs also face geographical limitations. In a centralized model, many coordination meetings are held in the capital cities, at a distance from where small HOs are generally based, which makes coordination highly time consuming (Knox Clarke and Campbell, 2015; IASC, 2020). A decentralized model, however, eliminates such travel burdens for small HOs. Small HOs also face technological barriers in coordination mechanisms where there is a high reliance on computers and the internet (Binder and Grünewald, 2010; Bolton, 2011; Knox Clarke and Campbell, 2015). A sub-coalition of small HOs without high reliance on computers and technology can significantly decrease the time they have to spend in coordination. Finally, small local HOs and large international HOs need to coordinate activities that do not involve the other type, e.g., operations in areas that only international members have access, which makes the time spent in centralized coordination meetings partly futile (Steets *et al.*, 2010).

Let us denote the level of centralization in the coordination mechanism by $\rho \in (0, 1]$. When $\rho = 1$, all the information from each member of each type is shared with all participants, i.e., the model is equivalent to the centralized model. As ρ decreases, the information is more aggregated in each sub-coalition and, therefore, the number of players of each type has a smaller impact on the response time of players of the other type. We define the decision vector of players type k as $\mathbf{x_k} = (x_{k1}, x_{k2}, \ldots, x_{kn_k})$ for $k = 1, 2$. Thus, the decision vector of all players is $\mathbf{x} = (\mathbf{x_1}, \mathbf{x_2})$. We further denote the vector of decisions of all players other than player i of type k as $\mathbf{x}_{-ki} = \mathbf{x} \setminus x_{ki}$ and the vector of decisions of all players of decision vector of type k players other than player i of type k as $\mathbf{x}_{k\setminus i} = \mathbf{x_k} \setminus x_{ki}$. The change in the utility of HO i of type k from joining the coordination mechanism is then calculated as

$$U_{Dki}(\mathbf{x}_{-ki}) = \alpha_k[N(\mathbf{x}_{k\setminus i}) + N(\mathbf{x}_{3-k})] - [(1 + N(\mathbf{x}_{k\setminus i}) + \rho N(\mathbf{x}_{3-k}))^{\beta} - 1] \qquad (3.3)$$

Therefore, the social welfare resulted from a coalition including a sub-coalition of y_1 players of type 1 and a sub-coalition of y_2 players of type 2 equals

$$\begin{aligned}\hat{U}_D(y_1, y_2) =& u_0 + \alpha_1 y_1^2 + \alpha_2 y_2^2 + (\alpha_1 + \alpha_2) y_1 y_2 - y_1 (y_1 + \rho y_2)^{\beta} - y_2 (y_2 + \rho y_1)^{\beta} \\ & - (\alpha_1 y_1 + \alpha_2 y_2) + y_1 + y_2\end{aligned}$$

and the gain in the utility of a player of type k from joining a sub-coalition of y_k players of type k that is communicating with a sub-coalition of y_{3-k} players of type $3 - k$ is

$$g_{Dk}(y_k, y_{3-k}) = \alpha_k (y_k + y_{3-k}) - (y_k + \rho y_{3-k})^{\beta} - (\alpha_k - 1), \qquad \forall k = 1, 2.$$

Note that we assume that the benefits in terms of resource utilization are independent from the level of centralization. In other words, we assume that the information sharing between the sub-coalitions is efficient. Although there can be information loss in the consolidation that occurs at each sub-coalition, we find this assumption to be reasonable as long as the sub-coalitions are ensured to communicate effectively. The chances of misinterpretation and translation errors are lower in a decentralized model since the information is aggregated at the sub-coalition level. Also, each type of HOs, e.g., small local HOs, is provided with a better platform to provide a comprehensive picture of their knowledge, expertise, and needs.

Proposition 6 *When the coordination mechanism gets decentralized, i.e., when ρ decreases, the number of coordinating HOs, the social optimal coalition size, and the optimal social welfare increase or remain the same.*

Decentralization allows HOs to spend less time coordinating their efforts with a larger number of HOs of a different type. Therefore, by decreasing the cost of coordination, it allows more HOs to join and gain the benefits from the shared information in the system. This especially encourages smaller HOs to participate in coordination as they are protected from the increase in response time due to the need to coordinate with a large number of members. Therefore, social welfare is also maximized where more HOs are involved in coordination. Decentralization not only allows more coordination, but it also leads to a better overall performance of the system, whether coordination time burden is high or low. This finding is in line with evaluations of effective engagements of local HOs that suggest structural changes to enhance coordination, underlining the differences between local and international actors that cannot be easily taken away (Knox Clarke and Campbell, 2015).

Proposition 7 *When $\beta < 1$ ($\beta > 1$), as the coordination mechanism gets more decentralized, i.e., when ρ decreases, the difference between the equilibrium solution and social optimal increases (decreases) or remains the same.*

This result shows that a central planner observes more benefits in decentralization than individual HOs. Decentralization enables HOs to benefit from better resource utilization and expected income while incurring lower costs. However, when time burden of coordination is low ($\beta < 1$), small HOs may still underestimate the collective benefits for all coordinating members. In these situations, a decentralized optimal coalition includes small HOs that are not included in the centralized optimal coalition. However, if marginal benefits of coordination for small HOs are smaller than a threshold, they still choose to operate alone. On ther other hand, when coordination time burden is high ($\beta > 1$), HOs underestimate the total time inefficiencies incurred for all participating HOs and form coalitions that are larger than optimal. As the mechanism gets decentralized, HOs are willing to join a larger coalition and the social optimal coalition size also increases. As a result of the collective benefits of decentralization for all HOs, the increase in the social optimal coalition size is larger than the increase in the equilibrium coalition size, leading to a coalition that is closer to the optimal.

3.7 Concluding Remarks

Given the lack of effective coordination in disaster response, we investigated horizontal coordination among HOs in centralized and decentralized models by developing a non-cooperative game theoretical model. Considering the roles of a comprehensive set of parameters in HOs' utility functions, our findings underline the important role of urgency and bureaucracy in coordination mechanisms. In urgent disaster response operations, time consuming bureaucratic coordination processes are the main obstacles to coordination, especially for small HOs. Our analysis shows that, in such situations, coordination beyond a level can even be harmful to the overall performance of the relief system as it slows down the response. We find that individual

HOs, that are focused on their own utilities, may underestimate the overall time costs and form coalitions that have more participants than optimal. On the contrary, if the coordination mechanism is efficient and does not involve a lot of bureaucracy, higher participation of HOs yields higher social welfare, a benefit that may be underestimated by individual HOs. We note that our model assumes that HOs' perception of the coordination mechanism is accurate. In other words, we assume that the central planner and HOs consider the same values for coordination time burden, β. It is possible that HOs perceive the mechanism to be more bureaucratic and time consuming than it actually is (Knox Clarke and Campbell, 2015). In that case, HOs overestimate the costs of coordination which could further decrease their participation.

In light of these findings, we further analyzed decentralization of coordination mechanisms such that small and large HOs are separated into communicating sub-coalitions. Our findings support the effectiveness of this structural change and show that it can lead to higher coordination levels and higher social welfare at all levels of urgency and bureaucracy since it can eliminate multiple obstacles to coordination, allowing for a more agile response. The benefits of decentralization are more pronounced in urgent response operations and when coordination mechanism is highly bureaucratic. In these situations, decentralization reduces HOs' divergence from the optimal solution and results in an outcome that is closer to the social optimal as compared the outcome of a centralized model.

Taken together, our findings highlight the importance of coordination mechanism design. It is predominantly assumed that maximum coordination should always be sought. However, our findings show that time efficiency of the coordination mechanism is a precondition for this assumption. A bureaucratic and time inefficient mechanism can make coordination harmful to the performance of the relief systems.

Further, we show that decentralization of coordination mechanisms can improve the time efficiency and therefore lead to more coordination and better performance.

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APPENDIX A

GOVERNANCE QUALITY VARIABLE

We follow Newton (2015) and define governance as a variable made up of four sub-indices: governing body, governing policies, compensation policies, and accountability. The components of each of these sub-indices are provided in Table A.1. For each organization-year observation, each sub-index score is calculated as the ratio between the sum of the component scores of that observation and the total possible score in that sub-index. Governance quality is then calculated as the average of the four sub-index scores.

In her cross-sectional analysis, Newton (2015) uses weights for each of the components based on the responses of all organizations in the data. However, our data spans over 8 years during which the responses varied significantly. Moreover, such weights would obscure our ability to capture an organization's decisions to change their governance quality and results in a measure that is a mix of the organization's decisions and the sector conditions (i.e., other organizations' decisions). We account for the sector conditions by using an instrumental variable that captures the governance quality of similar organizations.

Table A.1: Governance quality measure components

Governing body		
Board independence	Is at least two-thirds of the organization's board of directors independent? [VI.A.1b/VI.A.1a]	=1 if Yes =0 if No
Inside relationship	Did any person who is a current or former officer, director, trustee, or key employee have a direct business relationship with the organization [IV.28a], have a family member who has a direct or indirect business relationship with the organization [IV.28b], or serve as an officer, director, trustee, key employee, partner, or member of an entity doing business with the organization [IV.28c]?	=1 if No =0 if Yes
Outside management	Did the organization delegate control over management duties customarily performed by or under the direct supervision of officers, directors or trustees, or key employees to a management company or other person? [VI.A.3]	=1 if Yes =0 if No
Stockholders	Does the organization have members or stockholders [VI.A.6] who may elect one or more members of the governing body [VI.A.7a] and approve the decisions of the governing body [VI.A.7b]?	=1 if Yes =0 if No
Form 990	Was a copy of the Form 990 provided to the organization's governing body before it was filed? [VI.A.10]	=1 if Yes =0 if No
Governing policies		
Conflict of interest	Does the organization have a written conflict of interest policy? [VI.B.12a]	=1 if Yes =0 if No
Whistleblower	Does the organization have a written whistleblower policy? [VI.B.13]	=1 if Yes =0 if No
Document retention	Does the organization have a written document retention and destruction policy? [VI.B.14]	=1 if Yes =0 if No
Grant to officer	Did the organization provide a grant or other assistance to an officer, director, trustee, key employee, or substantial contributor, or to a person related to such an individual? [IV.27]	=1 if No =0 if Yes

Table A.1: Governance quality measure components (continued)

Compensation policies		
CEO Compensation	Indicate the number of ways that the organization uses to establish the compensation of the organization's CEO/Executive Director [Schedule J, I.3]. (There are six possibilities: compensation committee, independent compensation consultant, Form 990 of other organizations, written employment contract, compensation survey or study, and approval by the board or compensation committee.)	Continuous
Officer compensation	Did the process for determining compensation of the non-CEO officers or key employees of the organization include a review and approval by independent persons, comparability data, and contemporaneous substantiation of the deliberation and decision? [VI.B.15b]	=1 if Yes =0 if No
Reimbursement	If the organization provided fringe benefits to any person listed in the Schedule of Compensation to Officers, Directors, Trustees, Key Employees, and Highest Compensated Employees [Schedule J, I.1a], did the organization follow a written policy regarding payment or reimbursement or provision of all of the associated expenses [Schedule J, I.1b]?	=1 if Yes =0 if No
Substantiation	If the organization provided fringe benefits to any person listed in the Schedule of Compensation to Officers, Directors, Trustees, Key Employees, and Highest Compensated Employees [Schedule J, I.1a], did the organization require substantiation prior to reimbursing or allowing the associated expenses [Schedule J, I.2]?	=1 if Yes =0 if No
Accountability		
Website	Does the organization make its Form 1023 (or 1024 if applicable), 990, and 990-T available for public inspection on its own website? [VI.C.18]	=1 if Yes =0 if No
Independent audit	Were the organization's financial statements compiled, reviewed, or audited by an independent accountant? XI.2a–b] (If audited, the audit must not be a Circular A-133 audit [i.e., "No" to XI.3a])	=1 if Audited =0.5 if Reviewed or Compiled =0 if No
Audit committee	If the organization's financial statements are compiled, reviewed, or audited by an independent accountant [XI.2a–b], does the organization have a committee that assumes responsibility for oversight of the audit, review, or compilation of its financial statements and selection of an independent accountant [XI.2c]?	=1 if Yes =0 if No

APPENDIX B

RAW DATA DESCRIPTIVE STATISTICS

Table B.1 indicates summary statistics of the raw values of variables that are logged in our regressions.

Table B.1: Summary statistics and descriptions of variables (values in thousands USD)

Variable	Description	Mean	SD	Min	Max
Donations	Donations from individuals, corporations, and foundations	682.124	2464.919	0.000	132044.200
Assets	Total assets	5190.442	16919.900	0.001	982677.000
GovernmentGrants	Grants received from government entities	795.055	2940.013	0.000	75613.270
OwnIncome	Income from sources other than donations and grants	1792.119	5163.729	-31.036	89009.590
Earmarked	Total temporarily and permanently restricted assets	616.256	3760.383	0.000	186609.300
Fundraising	Fundraising expenses	54.625	217.648	0.000	12626.830
Liabilities	Total liabilities	2436.633	12592.900	-1160.118	769658.000
Occupancy	Total occupancy expenses	164.516	519.030	-342.126	47392.480

Note that reports of negative values for variables such as own income, liabilities, and occupancy expenses are not unexpected in the nonprofit sector. For instance, some organizations have suffered losses in their investments in some years and, thus, had negative own income. Andreoni and Payne (2011) also report negative values of liabilities and occupancy expenses in their data.

APPENDIX C

WITHIN-BETWEEN ESTIMATION

Given that a large proportion of variation of our variables is between nonprofits, we estimated a mixed-effects model, which separates the within- and between-nonprofit effects. For Equation 1.1, first, we added a random component to the slope of *PSR*. The LR test is significant, supporting the use of a random slope. Next, in addition to the random slope for PSR, we also included a random component in the slope of *governance*. The LR test similarly supports inclusion of this component. We then allow the random slopes to covary, using an unstructured covariance matrix. The LR test is insignificant, favoring the model without the covariance between random slopes. Therefore, we use random slopes for both *PSR* and *governance*. We take a similar approach for Equation 1.2, testing whether a random slope is needed for *governance*. The LR test is significant, supporting the use of a random slope. However, the LR test indicates that it is unnecessary to allow this random slope to covary with the intercept. Results of the within-between analysis, reported in Table C.1, confirm that PSR and governance increase donations, both within and between organizations. Moreover, as expected from the large proportion of variance between nonprofits, we find that the between effects are larger than the within effects for both variables. Results of both mixed-effects and fixed-effects estimations are consistent, but the mixed-effects results are not corrected for endogeneity.

Table C.1: Results of mixed-effects estimation.

	Within-organization	Between-organization
Dependent variable: $\log(Donations_{it})$		
PSR	0.0014 [p=0.038]	0.0105 [$p < 0.001$]
$Governance$	0.0021 [p=0.051]	0.0055 [$p < 0.001$]
$\log Fundraising$	0.0443 [$p < 0.001$]	0.2581 [$p < 0.001$]
$\log Assets$	-0.0198 [p=0.155]	0.1661 [$p < 0.001$]
$\log GovernmentGrants$	-0.0283 [$p < 0.001$]	-0.1160 [$p < 0.001$]
$\log OwnIncome$	-0.0458 [p=0.001]	-0.2175 [$p < 0.001$]
$\log Earmarked$	0.0033 [p=0.106]	0.0891 [$p < 0.001$]
$ProgramConcentration$	-0.1613 [p=0.003]	-1.6566 [$p < 0.001$]
$Year_t$	included	
Intercept	10.6046 [$p < 0.001$]	
$Var(PSR)$	0.0006 (0.0002)	
$Var(Governance)$	0.0044 (0.0006)	
$Var(Intercept)$	4.9068 (0.0617)	
Observations	174711	
Nonprofits	36754	
Wald test	23262.989 [p=0.000]	
Dependent variable: $\log(Donations_{it})$		
$Governance$	-0.0020 [p=0.736]	-0.0126 [p=0.053]
$\log Assets$	0.6417 [$p < 0.001$]	-0.4118 [$p < 0.001$]
$\log GovernmentGrants$	0.1023 [$p < 0.001$]	0.4000 [$p < 0.001$]
$\log OwnIncome$	1.2665 [$p < 0.001$]	1.1900 [$p < 0.001$]
$\log Earmarked$	0.0040 [p=0.683]	-0.0127 [p=0.427]
$ProgramConcentration$	-1.0779 [p=0.004]	-0.5422 [p=0.043]
$LiabilitiesToAssets$	0.0032 [p=0.063]	-0.0204 [p=0.013]
$ZeroFundraising$	2.9214 [$p < 0.001$]	4.9926 [$p < 0.001$]
$Year_t$	included	
Intercept	70.1190 [$p < 0.001$]	
$Var(Governance)$	0.3248 (0.0236)	
$Var(Intercept)$	194.4393 (3.4162)	
Observations	220971	
Nonprofits	38143	
Wald test	3304.699 [p=0.000]	

Numbers in parentheses show standard deviations. Within-nonprofit effects indicate the estimated coefficients of the nonprofit mean values of the variables and between-nonprofit effects indicate the estimated coefficients for nonprofit-centered (demeaned) variables.

APPENDIX D

GOVERNANCE QUALITY INSTRUMENTAL VARIABLE

We define our IV for governance quality similar to how Newton (2015) creates IVs for performance metrics. The IV for organization i in year t is the average governance quality score of organizations with similar size, within the same sector, region, and year, excluding organization i. Groups with fewer than five observations are excluded. The following categories are used:

- Size: Similar to Guidestar, we divide organizations based on their total expenses that approximate how much work an organization accomplishes in a year, rather than its ability to raise funds or generate revenue. We define the following size categories based on average total expenses in our data:
  - Grassroots: Less than or equal to 1M USD,
  - Small: More than 1M USD and less than or equal to 5M USD,
  - Medium: More than 5M USD and less than or equal to 10M USD,
  - Large: More than 10M USD.
- Sector: Social services or relief.
- Region: Geographical region in accordance with the U.S. Census Bureau's census codes: New England, Middle Atlantic, North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific.
- Year: Tax year.

APPENDIX E

ROBUSTNESS CHECKS-CHAPTER 1

Table E.1 indicates the results of 3SLS estimations of the full model when we use subsamples of the data, removing or adding organizations with extreme characteristics. The first (second) column shows the results when we remove nonprofits with an average PSR in the top or bottom 10 (25) percentiles of the data. The third column indicates the results when we remove organizations that never reported any positive fundraising expenses over the observation period. Column 4 shows the results when we exclude nonprofits that have more than two occurrences where they report zero fundraising expenses but positive donations in two consecutive years in our data, or have three consecutive years of reporting zero fundraising expenses and positive donations. Exclusion of these two categories of nonprofits follows Andreoni and Payne (2003). Column 5 indicates the results including the bottom percentile of own income values and observations with negative earmarked assets which we had removed as outliers from our main analysis.

Table E.1: Robustness checks of the results, extreme cases

Variable	Middle 80 centile of average PSR	Middle 50 centile of average PSR	Excluding always zero fundraising	Excluding consecutive obs. of donations without fundraising	Including negative earmarked and own income outliers
Dependent variable: $\log(Donations_{it})$					
$PSR_{i(t-1)}$	0.2957 [$p<0.001$]	0.3981 [$p<0.001$]	0.2909 [$p<0.001$]	0.0535 [p=0.046]	0.1559 [$p<0.001$]
$Governance_{i(t-1)}$	0.2416 [$p<0.001$]	0.2274 [$p<0.001$]	0.2061 [$p<0.001$]	0.1125 [p=0.018]	0.1400 [$p<0.001$]
$\log(Fundraising_{it})$	0.4499 [$p<0.001$]	0.6012 [$p<0.001$]	0.4477 [$p<0.001$]	0.4182 [$p<0.001$]	0.2598 [$p<0.001$]
$\log(Assets_{i(t-1)})$	-0.3844 [$p<0.001$]	-0.4565 [$p<0.001$]	-0.4507 [$p<0.001$]	-0.2084 [$p<0.001$]	-0.2386 [$p<0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0495 [$p<0.001$]	-0.0525 [$p<0.001$]	-0.0531 [$p<0.001$]	-0.0203 [$p<0.001$]	-0.0430 [$p<0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.3938 [$p<0.001$]	-0.4776 [$p<0.001$]	-0.4305 [$p<0.001$]	-0.1254 [p=0.006]	-1.7121 [$p<0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0112 [p=0.006]	-0.0097 [p=0.042]	-0.0144 [p=0.003]	-0.0089 [p=0.036]	-0.2312 [p=0.012]
$ProgramConcentration_{i(t-1)}$	0.0589 [p=0.502]	-0.0308 [p=0.789]	0.4615 [$p<0.001$]	0.1617 [p=0.083]	0.2657 [p=0.002]
$Year_t$	included	included	included	included	included
Observations	140462	88235	107187	95706	177494
χ^2 test	252.5944 [$p<0.001$]	201.3173 [$p<0.001$]	323.3256 [$p<0.001$]	293.1718 [$p<0.001$]	422.1097 [$p<0.001$]
Dependent variable: $PSR_{i(t-1)}$					
$Governance_{i(t-1)}$	-0.4566 [p=0.004]	-0.2980 [p=0.025]	-0.4377 [p=0.026]	-0.4300 [p=0.017]	-0.4067 [p=0.007]
$ZeroFundraising_{i(t-1)}$	2.7611 [$p<0.001$]	2.9888 [$p<0.001$]	2.5426 [$p<0.001$]	2.4581 [$p<0.001$]	2.5432 [$p<0.001$]
$LiabilityToAsset_{i(t-1)}$	0.0007 [p=0.675]	0.0002 [p=0.915]	-0.0044 [p=0.001]	-0.0042 [p=0.068]	0.0009 [p=0.364]
$\log(Assets_{i(t-1)})$	0.8724 [$p<0.001$]	0.7251 [$p<0.001$]	1.1450 [$p<0.001$]	1.1691 [$p<0.001$]	1.0711 [$p<0.001$]
$\log(GovernmentGrants_{i(t-1)})$	0.0836 [$p<0.001$]	0.0639 [$p<0.001$]	0.1358 [$p<0.001$]	0.1096 [$p<0.001$]	0.0975 [$p<0.001$]
$\log(OwnIncome_{i(t-1)})$	1.1149 [$p<0.001$]	0.9674 [$p<0.001$]	1.2485 [$p<0.001$]	1.3160 [$p<0.001$]	8.9529 [$p<0.001$]
$\log(Earmarked_{i(t-1)})$	0.0161 [p=0.182]	0.0093 [p=0.402]	0.0230 [p=0.190]	0.0363 [p=0.025]	0.6546 [p=0.097]
$ProgramConcentration_{i(t-1)}$	0.1862 [p=0.491]	0.3717 [p=0.183]	-1.0903 [p=0.002]	-0.5298 [p=0.135]	-1.6400 [$p<0.001$]
$Year_t$	included	included	included	included	included
Observations	140462	88235	107187	95706	177494
χ^2 test	2097.2388 [$p<0.001$]	1695.4895 [$p<0.001$]	1783.0176 [$p<0.001$]	1335.5361 [$p<0.001$]	1726.0622 [$p<0.001$]
Total Effect of $Governance_{i(t-1)}$	0.1066 [p=0.012]	0.1088 [p=0.013]	0.0788 [p=0.034]	0.0894 [p=0.033]	0.0766 [p=0.016]

Table E.2 summarizes the results when we modify the set of nonprofits in the sample based on their NTEE codes, i.e., type of their services. This approach is similar to the sensitivity analysis performed by Andreoni and Payne (2011).

Table E.3 includes the results when we make slight variations in our IV for governance quality. The first column reports the results when nonlinear term of the IV is included, a robustness check similar to that of Andreoni and Payne (2011). Next, we calculated the IV excluding geographical regions in our categorization of similar nonprofits, i.e., the IV is the average governance of organizations in the same size category and the same sector in the same year. Finally, column 3 shows the results when we use a more granular size categorization in our definition of similar nonprofits. In this modification, we use eight size categories, dividing each of the size buckets mentioned in Appendix D into two sub-categories, using the middle point of the thresholds.

Table E.4 illustrates robustness of our results to estimation methods. The first column shows the results when we use a system 2SLS method, which is different from 3SLS in that it assumes zero correlation between the errors of the two equations. The second column indicates the results of separate 2SLS estimations of the two equations.

Table E.2: Robustness checks of the results, excluding NTEE categories

Variable	Excluding environment organizations (C)	Excluding crime organizations (I)	Excluding employment organizations (J)	Excluding Food organizations (K)	Excluding housing organizations (L)	Excluding community organizations (S)	Excluding relief organizations (M, Q33)
Dependent variable: $\log(Donations_{it})$							
$PSR_{i(t-1)}$	0.1413 [$p < 0.001$]	0.1824 [$p < 0.001$]	0.1544 [$p < 0.001$]	0.1557 [$p < 0.001$]	0.3902 [$p < 0.001$]	0.1049 [$p < 0.001$]	0.1523 [$p < 0.001$]
$Governance_{i(t-1)}$	0.1574 [$p < 0.001$]	0.1603 [$p < 0.001$]	0.1397 [$p < 0.001$]	0.1386 [p=0.001]	0.2509 [$p < 0.001$]	0.1060 [p=0.005]	0.1601 [$p < 0.001$]
$\log(Fundraising_{it})$	0.2331 [$p < 0.001$]	0.2985 [$p < 0.001$]	0.2699 [$p < 0.001$]	0.2644 [$p < 0.001$]	0.5875 [$p < 0.001$]	0.1845 [$p < 0.001$]	0.2342 [$p < 0.001$]
$\log(Assets_{i(t-1)})$	-0.2128 [$p < 0.001$]	-0.2369 [$p < 0.001$]	-0.2156 [$p < 0.001$]	-0.2181 [$p < 0.001$]	-0.4474 [$p < 0.001$]	-0.1567 [$p < 0.001$]	-0.2155 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0443 [$p < 0.001$]	-0.0487 [$p < 0.001$]	-0.0449 [$p < 0.001$]	-0.0445 [$p < 0.001$]	-0.0652 [$p < 0.001$]	-0.0387 [$p < 0.001$]	-0.0445 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.2716 [$p < 0.001$]	-0.3444 [$p < 0.001$]	-0.2929 [$p < 0.001$]	-0.2911 [$p < 0.001$]	-0.5165 [$p < 0.001$]	-0.2112 [$p < 0.001$]	-0.2994 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0069 [p=0.028]	-0.0107 [p=0.002]	-0.0084 [p=0.008]	-0.0080 [p=0.014]	-0.0187 [$p < 0.001$]	-0.0036 [p=0.244]	-0.0080 [p=0.011]
$ProgramConcentration_{i(t-1)}$	0.2804 [p=0.003]	0.2976 [p=0.001]	0.2121 [p=0.008]	0.1870 [p=0.018]	0.5377 [$p < 0.001$]	0.1353 [p=0.098]	0.1951 [p=0.022]
$Year_t$	included	included	included	included	included	included	included
Observations	163795	165994	166487	168073	151200	152713	159174
χ^2 test	391.5471 [$p < 0.001$]	370.8682 [$p < 0.001$]	383.4072 [$p < 0.001$]	386.8365 [$p < 0.001$]	355.0598 [$p < 0.001$]	379.3297 [$p < 0.001$]	382.7138 [$p < 0.001$]
Dependent variable: $PSR_{i(t-1)}$							
$Governance_{i(t-1)}$	-0.3247 [p=0.043]	-0.3248 [p=0.045]	-0.3458 [p=0.033]	-0.2815 [p=0.095]	-0.2944 [p=0.105]	-0.2861 [p=0.092]	-0.3725 [p=0.019]
$ZeroFundraising_{i(t-1)}$	2.4866 [$p < 0.001$]	2.6047 [$p < 0.001$]	2.6474 [$p < 0.001$]	2.6782 [$p < 0.001$]	2.6739 [$p < 0.001$]	2.4538 [$p < 0.001$]	2.3230 [$p < 0.001$]
$LiabilityToAsset_{i(t-1)}$	0.0009 [p=0.357]	0.0001 [p=0.919]	0.0007 [p=0.476]	0.0007 [p=0.474]	-0.0018 [p=0.193]	0.0016 [p=0.119]	0.0008 [p=0.410]
$\log(Assets_{i(t-1)})$	0.8831 [$p < 0.001$]	0.8667 [$p < 0.001$]	0.9299 [$p < 0.001$]	0.8765 [$p < 0.001$]	0.8065 [$p < 0.001$]	0.8610 [$p < 0.001$]	0.8984 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	0.0963 [$p < 0.001$]	0.1014 [$p < 0.001$]	0.1056 [$p < 0.001$]	0.0992 [$p < 0.001$]	0.0978 [$p < 0.001$]	0.1003 [$p < 0.001$]	0.1063 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	1.3945 [$p < 0.001$]	1.4553 [$p < 0.001$]	1.4467 [$p < 0.001$]	1.3852 [$p < 0.001$]	1.0502 [$p < 0.001$]	1.3798 [$p < 0.001$]	1.4800 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	0.0204 [p=0.117]	0.0251 [p=0.073]	0.0220 [p=0.102]	0.0215 [p=0.113]	0.0177 [p=0.233]	0.0098 [p=0.489]	0.0218 [p=0.088]
$ProgramConcentration_{i(t-1)}$	-1.9083 [$p < 0.001$]	-1.2527 [$p < 0.001$]	-1.1781 [$p < 0.001$]	-1.0696 [$p < 0.001$]	-1.0334 [p=0.001]	-1.4330 [$p < 0.001$]	-1.2713 [$p < 0.001$]
$Year_t$	included	included	included	included	included	included	included
Observations	163795	165994	166487	168073	151200	152713	159174
χ^2 test	2075.1995 [$p < 0.001$]	2167.8457 [$p < 0.001$]	2194.0874 [$p < 0.001$]	2193.3239 [$p < 0.001$]	1607.0076 [$p < 0.001$]	1936.5623 [$p < 0.001$]	2007.3162 [$p < 0.001$]
$Governance_{i(t-1)}$ Total Effect	0.1115 [p=0.002]	0.1010 [p=0.005]	0.0863 [p=0.012]	0.0948 [p=0.011]	0.1360 [p=0.005]	0.0760 [p=0.036]	0.1034 [p=0.003]

Table E.3: Robustness checks of the results, IV variations

Variable	Nonlinear term	No geographic categorization	8 size categories
Dependent variable: $\log(Donations_{it})$			
$PSR_{i(t-1)}$	0.1346 [$p < 0.001$]	0.1381 [$p < 0.001$]	0.1629 [$p < 0.001$]
$Governance_{i(t-1)}$	0.1726 [$p < 0.001$]	0.2082 [$p < 0.001$]	0.1501 [$p < 0.001$]
$\log(Fundraising_{it})$	0.2234 [$p < 0.001$]	0.2163 [$p < 0.001$]	0.2741 [$p < 0.001$]
$\log(Assets_{i(t-1)})$	-0.2138 [$p < 0.001$]	-0.2391 [$p < 0.001$]	-0.2247 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0440 [$p < 0.001$]	-0.0455 [$p < 0.001$]	-0.0463 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.2726 [$p < 0.001$]	-0.2861 [$p < 0.001$]	-0.3061 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0096 [p=0.002]	-0.0118 [$p < 0.001$]	-0.0087 [p=0.004]
$ProgramConcentration_{i(t-1)}$	0.1989 [p=0.012]	0.2291 [p=0.005]	0.2214 [p=0.006]
$Year_t$	included	included	included
Observations	174419	174711	174251
χ^2 test	417.9065 [$p < 0.001$]	404.8526 [$p < 0.001$]	420.5528 [$p < 0.001$]
Dependent variable: $PSR_{i(t-1)}$			
$Governance_{i(t-1)}$	-0.4531 [p=0.002]	-0.5286 [p=0.001]	-0.4091 [p=0.004]
$ZeroFundraising_{i(t-1)}$	2.5368 [$p < 0.001$]	2.4821 [$p < 0.001$]	2.5656 [$p < 0.001$]
$LiabilityToAsset_{i(t-1)}$	0.0010 [p=0.317]	0.0010 [p=0.322]	0.0007 [p=0.470]
$\log(Assets_{i(t-1)})$	0.9624 [$p < 0.001$]	1.0106 [$p < 0.001$]	0.9334 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	0.1082 [$p < 0.001$]	0.1108 [$p < 0.001$]	0.1068 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	1.4419 [$p < 0.001$]	1.4573 [$p < 0.001$]	1.4297 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	0.0294 [p=0.024]	0.0335 [p=0.011]	0.0265 [p=0.036]
$ProgramConcentration_{i(t-1)}$	-1.3621 [$p < 0.001$]	-1.4176 [$p < 0.001$]	-1.3377 [$p < 0.001$]
$Year_t$	included	included	included
Observations	174419	174711	174251
χ^2 test	2176.4741 [$p < 0.001$]	2100.8981 [$p < 0.001$]	2202.5575 [$p < 0.001$]
$Governance_{i(t-1)}$ Total Effect	0.1116 [$p < 0.001$]	0.1352 [$p < 0.001$]	0.0835 [p=0.007]

Table E.4: Robustness checks of the results, estimation methods

Variable	System 2SLS	Separate 2SLS
Dependent variable: $\log(Donations_{it})$		
$PSR_{i(t-1)}$	0.0893 [p=0.003]	0.0066 [$p < 0.001$]
$Governance_{i(t-1)}$	0.1350 [$p < 0.001$]	0.1556 [p=0.017]
$\log(Fundraising_{it})$	0.1669 [$p < 0.001$]	0.5757 [p=0.001]
$\log(Assets_{i(t-1)})$	-0.1558 [$p < 0.001$]	-0.1497 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0381 [$p < 0.001$]	-0.0400 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	-0.2000 [$p < 0.001$]	-0.1333 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	-0.0067 [p=0.035]	-0.0127 [p=0.003]
$ProgramConcentration_{i(t-1)}$	0.1081 [p=0.186]	0.1487 [p=0.105]
$Year_t$	included	included
Observations	174419	173210
χ^2 test (F test)	25.4929 [$p < 0.001$]	14.3609 [$p < 0.001$]
Underidentification LM test		26.2093 [$p < 0.001$]
Dependent variable: $PSR_{i(t-1)}$		
$Governance_{i(t-1)}$	-0.4227 [p=0.008]	-0.8255 [$p < 0.001$]
$ZeroFundraising_{i(t-1)}$	0.0032 [p=0.003]	2.3377 [$p < 0.001$]
$LiabilityToAsset_{i(t-1)}$	2.5459 [$p < 0.001$]	0.0041 [p=0.052]
$\log(Assets_{i(t-1)})$	0.9562 [$p < 0.001$]	1.1470 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	0.1071 [$p < 0.001$]	0.1375 [$p < 0.001$]
$\log(OwnIncome_{i(t-1)})$	1.4326 [$p < 0.001$]	1.6009 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	0.0272 [p=0.040]	0.0666 [p=0.001]
$ProgramConcentration_{i(t-1)}$	-1.3372 [$p < 0.001$]	-2.1075 [$p < 0.001$]
$Year_t$	included	included
Observations	174419	219598
χ^2 test (F test)	150.5964 [$p < 0.001$]	63.4263 [$p < 0.001$]
Underidentification LM test		54.0128 [$p < 0.001$]
$Governance_{i(t-1)}$ Total Effect	0.0972 [p=0.015]	

APPENDIX F

FIRST STAGE ESTIMATES

Table F.1 shows the results of the first stage estimates of the full model.

Table F.1: First stage estimates of the full model

Dependent variable:	$\log(Donations_{it})$	$PSR_{i(t-1)}$	$\log(Fundraising_{it})$	$Governance_{i(t-1)}$
$\log(OwnIncome_{i(t-1)})$	-0.0422 [$p < 0.001$]	1.3163 [$p < 0.001$]	0.0424 [$p < 0.001$]	0.2529 [$p < 0.001$]
$\log(Assets_{i(t-1)})$	-0.0065 [p=0.529]	0.6976 [$p < 0.001$]	0.0803 [$p < 0.001$]	0.5929 [$p < 0.001$]
$\log(GovernmentGrants_{i(t-1)})$	-0.0244 [$p < 0.001$]	0.0923 [$p < 0.001$]	0.0065 [p=0.001]	0.0332 [$p < 0.001$]
$\log(Earmarked_{i(t-1)})$	0.0030 [p=0.104]	0.0018 [p=0.839]	0.0083 [$p < 0.001$]	0.0598 [$p < 0.001$]
$ProgramConcentration_{i(t-1)}$	-0.1346 [p=0.008]	-0.9515 [$p < 0.001$]	-0.2399 [$p < 0.001$]	-0.8897 [$p < 0.001$]
$LiabilityToAsset_{i(t-1)}$	-0.0006 [p=0.004]	0.0025 [p=0.012]	0.0000 [p=1.000]	0.0016 [p=0.010]
$ZeroFundraising_{i(t-1)}$	-0.1362 [$p < 0.001$]	2.8089 [$p < 0.001$]	-1.8522 [$p < 0.001$]	-0.6136 [$p < 0.001$]
$\log(Occupancy_{it})$	0.3055 [$p < 0.001$]	0.6877 [p=0.001]	0.4069 [$p < 0.001$]	0.5178 [$p < 0.001$]
$GovernanceIV_{i(t-1)}$	0.0173 [p=0.030]	-0.1705 [$p < 0.001$]	-0.0102 [p=0.258]	0.2254 [$p < 0.001$]
$Year_t$	included	included	included	included
Observations	174419	174419	174419	174419
χ^2 test	556.5555 [$p < 0.001$]	2439.2850 [$p < 0.001$]	8666.2705 [$p < 0.001$]	5387.8609 [$p < 0.001$]

APPENDIX G

ROBUSTNESS CHECKS-CHAPTER 2

Tables G.1 and G.2 indicate the results of HBIV estimations of Equation (2.1) and FE estimates of Equation (2.2) using subsamples of the data, respectively. The first columns report the results for a subsample where reported administrative expenses are positive. The second columns indicate the results where nonprofits that never reported any positive fundraising expenses over the observation period are excluded. In the third columns, a subsample is used where, following Andreoni and Payne (2003), we exclude nonprofits that have more than two occurrences where they report zero fundraising expenses but positive donations in two consecutive years in our data, or have three consecutive years of reporting zero fundraising expenses and positive donations. We note that GEE estimates of Equation (2.2) for these subsamples do not converge.

Table G.1: Heteroskedasticity-based instrumental variable (HBIV) estimations for revenue for subsamples of data

Variable	Positive administrative expenses	Excluding consecutive obs. of donations without fundraising	Excluding previous two categories	Excluding always zero fundraising
$\sinh^{-1}(Grants_{i(t-1)})$	0.0151 [$p < 0.001$]	0.0169 [$p < 0.001$]	0.0183 [$p < 0.001$]	0.0190 [$p < 0.001$]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0435 [$p < 0.001$]	0.0459 [$p < 0.001$]	0.0514 [$p < 0.001$]	0.0501 [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0002 [p=0.422]	0.0002 [p=0.337]	0.0004 [p=0.123]	0.0003 [p=0.223]
$\sinh^{-1}(FixedAssets_{it})$	0.0103 [$p < 0.001$]	0.0095 [$p < 0.001$]	0.0102 [$p < 0.001$]	0.0093 [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0035 [$p < 0.001$]	0.0033 [$p < 0.001$]	0.0027 [$p < 0.001$]	0.0029 [$p < 0.001$]
$DonationDependence_{it}$	0.0027 [$p < 0.001$]	0.0027 [$p < 0.001$]	0.0029 [$p < 0.001$]	0.0027 [$p < 0.001$]
$GovernmentDependence_{it}$	0.0038 [$p < 0.001$]	0.0038 [$p < 0.001$]	0.0036 [$p < 0.001$]	0.0038 [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0115 [$p < 0.001$]	0.0113 [$p < 0.001$]	0.0166 [$p < 0.001$]	0.0167 [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0797 [$p < 0.001$]	-0.0581 [$p < 0.001$]	-0.0446 [p=0.009]	-0.0423 [p=0.014]
$RevenueConcentration_{it}$	0.2328 [$p < 0.001$]	0.2520 [$p < 0.001$]	0.2680 [$p < 0.001$]	0.2787 [$p < 0.001$]
$Year_t$	included	included	included	included
Observations	152149	101410	90464	84121
F-test	335.1037 [$p < 0.001$]	315.8630 [$p < 0.001$]	300.6824 [$p < 0.001$]	299.8544 [$p < 0.001$]
Underidentification test	146.4413 [$p < 0.001$]	130.8522 [$p < 0.001$]	104.6676 [$p < 0.001$]	104.6992 [$p < 0.001$]
Hansen J test	20.8885 [p=0.1045]	11.5785 [p=0.6401]	10.8797 [p=0.6955]	10.3933 [p=0.7329]

Similarly, Tables G.3 and G.4 summarize the results using subsamples of data based on nonprofits' National Taxonomy of Exempt Entities (NTEE) codes, i.e., type of their services.

Table G.5 reports estimation results of Equation (2.1) using FE estimation without IVs, 2SLS IV estimation using an external IV (the average amount of grants that nonprofits in the same sector, size category, and geographical region provided to other organizations in the given year), and HBIV estimates using both this external IV and heteroskedasticity based IVs. We note that the external IV is only weakly correlated with grants. The Kleibergen-Paap rk Wald F statistic equals 5.00 which warns us about weak identification that can lead to more bias (Stock and Yogo, 2005).

Table G.6 report estimation results of Equation (2.2) using a Poisson pseudo-maximum likelihood estimation which provides reliable estimates when the dependent variable takes on the value of zero in a large portion of data (Santos Silva and Tenreyro, 2006).

Finally, Table G.7 shows FE estimation results of Equation (2.3) for a subset of nonprofits that received grants in at least one year of data.

Table G.2: Fixed-effects estimations for grants for subsamples of data

Variable	Positive administrative expenses	Excluding consecutive obs. of donations without fundraising	Excluding previous two categories	Excluding always zero fundraising
$RevenueGrowth_{it}$	0.0015 [$p < 0.001$]	0.0011 [p=0.018]	0.0014 [p=0.011]	0.0012 [p=0.031]
$DonationDependence_{it}$	0.0059 [p=0.020]	0.0038 [p=0.238]	0.0033 [p=0.363]	0.0043 [p=0.234]
$GovernmentDependence_{it}$	0.0228 [$p < 0.001$]	0.0218 [$p < 0.001$]	0.0194 [$p < 0.001$]	0.0227 [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0109 [p=0.061]	0.0105 [p=0.111]	0.0076 [p=0.267]	0.0079 [p=0.252]
$\sinh^{-1}(FixedAssets_{it})$	0.0333 [p=0.059]	0.0375 [p=0.062]	0.0546 [p=0.012]	0.0517 [p=0.019]
$\sinh^{-1}(Earmarked_{it})$	0.0618 [$p < 0.001$]	0.0628 [$p < 0.001$]	0.0748 [$p < 0.001$]	0.0756 [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0434 [p=0.002]	0.0467 [p=0.001]	0.0250 [p=0.149]	0.0252 [p=0.145]
$ProgramConcentration_{it}$	-1.6664 [$p < 0.001$]	-1.4290 [$p < 0.001$]	-1.5653 [$p < 0.001$]	-1.4052 [p=0.001]
$RevenueConcentration_{it}$	-0.0672 [p=0.818]	0.0710 [p=0.841]	0.4530 [p=0.236]	0.3702 [p=0.344]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	-0.2330 [$p < 0.001$]	-0.2143 [$p < 0.001$]	-0.2619 [$p < 0.001$]	-0.2401 [$p < 0.001$]
$Year_t$	included	included	included	included
Observations	39446	27776	24030	23237
F test	17.6851 [$p < 0.001$]	12.9155 [$p < 0.001$]	11.0017 [$p < 0.001$]	10.4283 [$p < 0.001$]

Table G.3: Heteroskedasticity-based instrumental variable (HBIV) estimations for revenue for subsamples of data excluding nonprofit subsectors

Variable	Excluding environment organizations (C)	Excluding crime organizations (I)	Excluding employment organizations (J)	Excluding Food organizations (K)	Excluding housing organizations (L)	Excluding community organizations (S)	Excluding relief organizations (M, Q33)
$\sinh^{-1}(Grants_{i(t-1)})$	0.0167 [$p < 0.001$]	0.0142 [$p < 0.001$]	0.0144 [$p < 0.001$]	0.0149 [$p < 0.001$]	0.0164 [$p < 0.001$]	0.0176 [$p < 0.001$]	0.0139 [$p < 0.001$]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0397 [$p < 0.001$]	0.0398 [$p < 0.001$]	0.0389 [$p < 0.001$]	0.0394 [$p < 0.001$]	0.0373 [$p < 0.001$]	0.0443 [$p < 0.001$]	0.0435 [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0002 [p=0.265]	0.0003 [p=0.135]	0.0003 [p=0.123]	0.0003 [p=0.128]	0.0003 [p=0.118]	0.0004 [p=0.059]	0.0004 [p=0.084]
$\sinh^{-1}(FixedAssets_{it})$	0.0103 [$p < 0.001$]	0.0108 [$p < 0.001$]	0.0106 [$p < 0.001$]	0.0106 [$p < 0.001$]	0.0092 [$p < 0.001$]	0.0111 [$p < 0.001$]	0.0115 [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0032 [$p < 0.001$]	0.0033 [$p < 0.001$]	0.0033 [$p < 0.001$]	0.0032 [$p < 0.001$]	0.0033 [$p < 0.001$]	0.0030 [$p < 0.001$]	0.0033 [$p < 0.001$]
$DonationDependence_{it}$	0.0024 [$p < 0.001$]	0.0028 [$p < 0.001$]	0.0027 [$p < 0.001$]	0.0026 [$p < 0.001$]	0.0028 [$p < 0.001$]	0.0027 [$p < 0.001$]	0.0029 [$p < 0.001$]
$GovernmentDependence_{it}$	0.0033 [$p < 0.001$]	0.0039 [$p < 0.001$]	0.0039 [$p < 0.001$]	0.0037 [$p < 0.001$]	0.0039 [$p < 0.001$]	0.0036 [$p < 0.001$]	0.0039 [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0110 [$p < 0.001$]	0.0113 [$p < 0.001$]	0.0115 [$p < 0.001$]	0.0114 [$p < 0.001$]	0.0116 [$p < 0.001$]	0.0105 [$p < 0.001$]	0.0117 [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0941 [$p < 0.001$]	-0.0754 [$p < 0.001$]	-0.0817 [$p < 0.001$]	-0.0835 [$p < 0.001$]	-0.0829 [$p < 0.001$]	-0.0822 [$p < 0.001$]	-0.0854 [$p < 0.001$]
$RevenueConcentration_{it}$	0.1564 [$p < 0.001$]	0.2212 [$p < 0.001$]	0.2237 [$p < 0.001$]	0.2170 [$p < 0.001$]	0.2286 [$p < 0.001$]	0.2195 [$p < 0.001$]	0.2305 [$p < 0.001$]
$Year_t$	included	included	included	included	included	included	included
Observations	153567	155461	156006	157410	141583	143356	148999
F-test	309.6655 [p=]	304.2161 [p=]	308.1308 [p=]	311.3573 [p=]	290.0435 [p=]	323.7594 [p=]	312.7697 [$p < 0.001$]
Underidentification test	142.6297 [$p < 0.001$]	146.0423 [$p < 0.001$]	151.5753 [$p < 0.001$]	152.1273 [$p < 0.001$]	139.8819 [$p < 0.001$]	136.5148 [$p < 0.001$]	154.8839 [$p < 0.001$]
Hansen J test	13.8649 [p=0.4598]	18.1340 [p=0.2007]	17.7790 [p=0.2170]	20.0660 [p=0.1281]	18.3242 [p=0.1924]	15.4032 [p=0.3512]	20.9772 [p=0.1022]

Table G.4: Fixed-effects (FE) estimations for grants for subsamples of data excluding nonprofit subsectors

Variable	Excluding environment organizations (C)	Excluding crime organizations (I)	Excluding employment organizations (J)	Excluding Food organizations (K)	Excluding housing organizations (L)	Excluding community organizations (S)	Excluding relief organizations (M, Q33)
$RevenueGrowth_{it}$	0.0014 [$p < 0.001$]	0.0016 [$p < 0.001$]	0.0015 [$p < 0.001$]	0.0014 [$p < 0.001$]	0.0014 [$p < 0.001$]	0.0016 [$p < 0.001$]	0.0013 [$p < 0.001$]
$DonationDependence_{it}$	0.0051 [p=0.042]	0.0046 [p=0.056]	0.0054 [p=0.026]	0.0045 [p=0.063]	0.0045 [p=0.076]	0.0072 [p=0.009]	0.0053 [p=0.033]
$GovernmentDependence_{it}$	0.0180 [$p < 0.001$]	0.0186 [$p < 0.001$]	0.0202 [$p < 0.001$]	0.0201 [$p < 0.001$]	0.0201 [$p < 0.001$]	0.0217 [$p < 0.001$]	0.0193 [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0118 [p=0.050]	0.0127 [p=0.028]	0.0115 [p=0.049]	0.0125 [p=0.032]	0.0099 [p=0.104]	0.0113 [p=0.070]	0.0146 [p=0.017]
$\sinh^{-1}(FixedAssets_{it})$	0.0223 [p=0.214]	0.0327 [p=0.061]	0.0318 [p=0.069]	0.0326 [p=0.060]	0.0394 [p=0.028]	0.0060 [p=0.751]	0.0349 [p=0.060]
$\sinh^{-1}(Earmarked_{it})$	0.0605 [$p < 0.001$]	0.0604 [$p < 0.001$]	0.0615 [$p < 0.001$]	0.0580 [$p < 0.001$]	0.0595 [$p < 0.001$]	0.0552 [$p < 0.001$]	0.0626 [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0493 [$p < 0.001$]	0.0513 [$p < 0.001$]	0.0502 [$p < 0.001$]	0.0484 [$p < 0.001$]	0.0461 [p=0.001]	0.0375 [p=0.014]	0.0467 [p=0.001]
$ProgramConcentration_{it}$	-1.9451 [$p < 0.001$]	-1.8260 [$p < 0.001$]	-1.7368 [$p < 0.001$]	-1.7367 [$p < 0.001$]	-1.6445 [$p < 0.001$]	-1.6778 [$p < 0.001$]	-1.7851 [$p < 0.001$]
$RevenueConcentration_{it}$	-0.1182 [p=0.689]	-0.2570 [p=0.369]	-0.0838 [p=0.767]	-0.1550 [p=0.584]	-0.1978 [p=0.504]	0.1955 [p=0.539]	-0.0234 [p=0.937]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	-0.2515 [$p < 0.001$]	-0.2426 [$p < 0.001$]	-0.2417 [$p < 0.001$]	-0.2295 [$p < 0.001$]	-0.2353 [$p < 0.001$]	-0.2595 [$p < 0.001$]	-0.2478 [$p < 0.001$]
$Year_t$	included	included	included	included	included	included	included
Observations	38105	39752	40369	40306	37242	33926	37534
F test	19.5388 [$p < 0.001$]	20.0996 [$p < 0.001$]	19.4005 [$p < 0.001$]	18.2565 [$p < 0.001$]	17.1829 [$p < 0.001$]	16.0640 [$p < 0.001$]	18.0236 [$p < 0.001$]

Table G.5: Estimation results for revenue using different methods

Variable	FE	HBIV	2SLS
$\sinh^{-1}(Grants_{i(t-1)})$	0.0025 [$p < 0.001$]	-0.0894 [p=0.200]	0.0131 [$p < 0.001$]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0381 [$p < 0.001$]	0.0188 [p=0.021]	0.0304 [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0003 [p=0.175]	0.0002 [p=0.312]	0.0001 [p=0.564]
$\sinh^{-1}(FixedAssets_{it})$	0.0106 [$p < 0.001$]	0.0040 [$p < 0.001$]	0.0042 [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0034 [$p < 0.001$]	0.0022 [p=0.002]	0.0014 [$p < 0.001$]
$DonationDependence_{it}$	0.0027 [$p < 0.001$]	0.0027 [$p < 0.001$]	0.0027 [$p < 0.001$]
$GovernmentDependence_{it}$	0.0038 [$p < 0.001$]	0.0039 [$p < 0.001$]	0.0038 [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0117 [$p < 0.001$]	0.0109 [$p < 0.001$]	0.0093 [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0856 [$p < 0.001$]	-0.0808 [$p < 0.001$]	-0.0649 [$p < 0.001$]
$RevenueConcentration_{it}$	0.2204 [$p < 0.001$]	0.2128 [$p < 0.001$]	0.2169 [$p < 0.001$]
$Year_t$	included	included	included
Observations	163308	163033	163033
F-test	208.1304 [$p < 0.001$]	248.8890 [$p < 0.001$]	339.1446 [$p < 0.001$]
Underidentification test	[$p < 0.001$]	5.7917 [$p < 0.001$]	161.7769 [$p < 0.001$]
Hansen J test	[$p < 0.001$]	[$p < 0.001$]	26.8520 [p=0.0300]

Table G.6: Poisson pseudo-maximum likelihood estimation results for grants. (Numbers in parentheses show robust standard deviations.)

Dependent variable: $\sinh^{-1}(Grants_{it)})$	
$RevenueGrowth_{it}$	0.0015 (0.0002) [$p < 0.001$]
$DonationDependence_{it}$	-0.0024 (0.0020) [p=0.235]
$GovernmentDependence_{it}$	0.0074 (0.0022) [p=0.001]
$\sinh^{-1}(Reserves_{it})$	0.0163 (0.0033) [$p < 0.001$]
$\sinh^{-1}(FixedAssets_{it})$	0.0353 (0.0061) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0117 (0.0046) [p=0.012]
$\sinh^{-1}(Fundraising_{it})$	-0.0075 (0.0061) [p=0.220]
$ProgramConcentration_{it}$	0.6832 (0.1737) [$p < 0.001$]
$RevenueConcentration_{it}$	0.4721 (0.1723) [p=0.006]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	-0.0468 (0.0110) [$p < 0.001$]
$Year_t$	included
Observations	39309
χ^2 test	270.6740 [$p < 0.001$]

Table G.7: Fixed-effects estimation results for administrative costs. (Numbers in parentheses show robust standard deviations.)

Dependent variable: $\sinh^{-1}(AdministrativeCost_{it})$	
$GrantIncomeDummy_{it}$	-0.0315 (0.0189) [p=0.096]
$\sinh^{-1}(GrantIncome_{it})$	0.0044 (0.0018) [p=0.012]
$\sinh^{-1}(Donations_{i(t-1)})$	0.0027 (0.0005) [$p < 0.001$]
$\sinh^{-1}(GovernmentGrants_{i(t-1)})$	0.0070 (0.0008) [$p < 0.001$]
$\sinh^{-1}(OwnIncome_{i(t-1)})$	0.0099 (0.0010) [$p < 0.001$]
$\sinh^{-1}(Grants_{i(t-1)})$	0.0024 (0.0009) [p=0.008]
$\sinh^{-1}(ProgramExpenses_{i(t-1)})$	0.0287 (0.0071) [$p < 0.001$]
$\sinh^{-1}(Fundraising_{it})$	0.0064 (0.0013) [$p < 0.001$]
$\sinh^{-1}(FixedAssets_{it})$	0.0246 (0.0017) [$p < 0.001$]
$\sinh^{-1}(Reserves_{it})$	0.0023 (0.0004) [$p < 0.001$]
$\sinh^{-1}(Earmarked_{it})$	0.0078 (0.0007) [$p < 0.001$]
$ProgramConcentration_{it}$	-0.0658 (0.0248) [p=0.008]
$RevenueConcentration_{it}$	0.0409 (0.0226) [p=0.070]
$Year_t$	included
Observations	105886
F test	99.7734 [$p < 0.001$]

APPENDIX H

PROOFS

Theorem 1

Player i joins a cluster if and only if it increases its utility, i.e., if $U_i(\mathbf{x}_{-i}) > 0$. Therefore, player i joins a cluster of $y-1$ HOs if

$$U_i(\mathbf{x}_{-i}) = \alpha_i(y-1) - \big([1+y-1]^\beta - 1\big) > 0 \Rightarrow \alpha_i > \frac{y^\beta - 1}{y-1}.$$

Proposition 1

When decision making is myopic, players of type 1 will not form a coalition unless $g_1(2) > 0$. For $k = 1, 2$ we have

$$g_k^{'}(y) = \alpha_k - \beta y^{\beta-1}$$
$$g_k^{''}(y) = -\beta(\beta-1)y^{\beta-2}.$$

Therefore, if $g_1(2) > 0$, $g_1(y)$ is increasing convex for all $y_1 \geq 2$ and therefore $y_1^* = n_1$ is the utility-dominant equilibrium. We have $g_1(2) > 0$ if $\alpha_1 > 2^\beta - 1$.

Then, among players of type 2 that are next in the sequence, knowing that y_1^* players are in the coalition, a number equal to y_2^* will join such that $g_2(y_1^* + y_2^*) = 0$, if $g_2(y_1^*) > 0$, i.e., if

$$\alpha_2 > \frac{y_1^{*\beta} - 1}{y_1^* - 1} \tag{H.1}$$

Therefore, when $\alpha_1 > 2^\beta - 1$, if we also have $\alpha_2 > \dfrac{{n_1}^\beta - 1}{n_1 - 1}$, then a number of $y_2^* = n_2$ players of type 2 will join the coalition. Note that $g_2^{'}(n_1 + y_2) = \alpha_2 - \beta(n_1 + y_2)^{\beta-1} > 0$ when (H.1) holds. Also, we have $\dfrac{{n_1}^\beta - 1}{n_1 - 1} < 1$. Therefore, if $\dfrac{{n_1}^\beta - 1}{n_1 - 1} < \alpha_2 < 1 < \alpha_1$ a sequence where players with α_2 precede leads to a smaller coalition than the opposite sequence where players with α_1 join first. When considered first in the sequence, players with α_2 decide not to join the coalition, but they all would join if they know players of type 1 are in the coalition.

Proposition 2

We first consider the case that only HOs of type 2 are in considered. We have

$$\hat{U}_{y_2}^{'}(0, y_2) = \frac{\partial \hat{U}(0, y_2)}{\partial y_2} = 2\alpha_2 y_2 - (\beta+1)y_2^\beta - \alpha_2 + 1$$
$$\hat{U}_{y_2}^{''}(0, y_2) = \frac{\partial^2 \hat{U}(0, y_y)}{\partial y_2^2} = 2\alpha_2 - (\beta+1)\beta y_2^{\beta-1}$$

When $\beta < 1$, we have $\lim_{y_2 \to \infty} \hat{U}_{y_2}^{'}(0, y_2) = \infty$. Therefore, ignoring the constraint on the number of players, the social optimal coalition size equals ∞ at any value of $\alpha_2 > 0$.

Further, if

$$\alpha_2 > \beta \tag{H.2}$$

We have $\hat{U}'_{y_2}(0,1) = \alpha_2 - \beta > 0$, and

$$\frac{\beta+1}{2} < 1 < \frac{\alpha_2}{\beta} \tag{H.3}$$

Note that

$$\hat{U}''_{y_2}(0,y_2) = 2\beta\Big(\frac{\alpha_2}{\beta} - (\frac{\beta+1}{2})(\frac{1}{y_2})^{1-\beta}\Big).$$

Therefore $\hat{U}''_{y_2}(0,1) > 0$, and $\hat{U}''_{y_2}(0,y_2)$ is increasing in y_2. Thus, $\hat{U}(0,y_2)$ is convex increasing for all $y_2 \geq 1$ and therefore the optimal coalition includes all n_2 HOs of type 2 for any $\alpha_2 > \beta$ and $n_2 > 1$.

If $\alpha_2 < \beta$, then $\hat{U}(0,y_2)$ is initially decreasing concave at $y_2 = 1$ ($\hat{U}(0,1) = u_0$). As y_2 continues to increase, $\hat{U}(0,y_2)$ shifts to convex decreasing, and after reaching a local minimum, it eventually becomes increasing convex. Therefore, the social optimal coalition includes n_2 HOs of type 2 as long as $\hat{U}(0,n_2) > u_0$. For a given n_2, we have

$$\hat{U}(0,n_2) - u_0 = \alpha_2 n_2^2 - (\alpha_2 - 1)n - n^{\beta+1} > 0 \Rightarrow \alpha_2 > \frac{n_2^\beta - 1}{n_2 - 1}$$

Note that $\dfrac{n_2^\beta - 1}{n_2 - 1} < \beta$ for $n_2 > 1$ and $\beta < 1$. Also note that, since $\beta < 1$, the minimum threshold for α to make a coalition of all n_2 HOs the social optimal is smaller for larger values of n_2. In other words, if $\beta < 1$ and we have a large enough pool of players of the same type, the social optimal is to form a coalition including all players even when the marginal benefits of coordination are very low.

If $\alpha_2 \leq \dfrac{n_2^\beta - 1}{n_2 - 1}$, we have $\hat{U}(0,y_2) \leq u_0$ for all $y_2 > 1$. Therefore, the social optimal solution is to have no coalition.

We now consider the case where two types of HOs are considered simultaneously. Note that

$$\nabla\hat{U}(y_1,y_2) = \begin{pmatrix} \alpha_1(y_1+y_2) - (\beta+1)(y_1+y_2)^\beta + \alpha_1 y_1 + \alpha_2 y_2 - \alpha_1 + 1 \\ \alpha_2(y_1+y_2) - (\beta+1)(y_1+y_2)^\beta + \alpha_1 y_1 + \alpha_2 y_2 - \alpha_2 + 1 \end{pmatrix}$$

$$H(y_1,y_2) = \begin{pmatrix} 2\beta\Big(\dfrac{\alpha_1}{\beta} - \dfrac{\beta+1}{2}(y_1+y_2)^{\beta-1}\Big) & \alpha_1 + \alpha_2 - \beta(\beta+1)(y_1+y_2)^{\beta-1} \\ \alpha_1 + \alpha_2 - \beta(\beta+1)(y_1+y_2)^{\beta-1} & 2\beta\Big(\dfrac{\alpha_2}{\beta} - \dfrac{\beta+1}{2}(y_1+y_2)^{\beta-1}\Big) \end{pmatrix}$$

We have $\nabla \hat{U}(y_1, y_2) = \mathbf{0}$ at the unique point $(y_1^c, y_2^c) = (\frac{\alpha_2 - \beta}{\alpha_2 - \alpha_1}, \frac{\beta - \alpha_1}{\alpha_2 - \alpha_1})$ where $y_1^c + y_2^c = 1$. At this point

$$\det(H(y_1^c, y_2^c)) = -\beta(\beta + 1)(\alpha_1 + \alpha_2) - (\alpha_1 - \alpha_2)^2 < 0$$

and $\hat{U}(y_1^c, y_2^c) = u_0$. Therefore, the bivariate social welfare function has a unique critical point which is a saddle point and is outside of the space where a cluster is feasible (i.e., outside of $y_1 + y_2 > 1$). Therefore, the maximum may be the extremes of ∞ and $-\infty$ for y_1 and y_2.

If $\alpha_2 > \alpha_1 > \beta$ and $\beta < 1$, at any point where $y_1 + y_2 \geq 1$, we have $\nabla \hat{U}(y_1, y_2) > \mathbb{1}$, i.e., the social welfare function is increasing in y_1 and y_2 at any value of the variables over the decision space. Therefore, the social optimal coalition occurs at (∞, ∞). Considering the limits on the number of players, $(y_1^o, y_2^o) = (n_1, n_2)$.

Note that if $\beta < 1$ and $\alpha_2 < \beta$, $\hat{U}(y_1, n_2)$ is either increasing convex in y_2 at any $y_2 \geq 1$ or it eventually becomes increasing convex in y_2. Therefore $(y_1^o, y_2^o) = (n_1, n_2)$ as long as $\hat{U}(n_1, n_2) - \hat{U}(n_1, 0) > 0$. Defining $\Delta_2(y_1, y_2) = \hat{U}(y_1, y_2) - \hat{U}(0, y_2)$ we have

$$\Delta_2(y_1, y_2) = \alpha_2 y_2^2 + (1 - \alpha_2) y_2 + (\alpha_1 + \alpha_2) y_1 y_2 + y_1^{\beta+1} - (y_1 + y_2)^{\beta+1}.$$

Note that

$$\begin{aligned}
\frac{\partial \Delta_2(y_1, y_2)}{\partial \alpha_2} &= y_2^2 + (y_1 - 1) y_2 > 0 \\
\frac{\partial \Delta_2(y_1, y_2)}{\partial \alpha_2 \partial y_1} &= y_2 > 0
\end{aligned}$$

The same holds for $\Delta_1(y_1, y_2) = \hat{U}(y_1, y_2) - \hat{U}(0, y_2)$ when $\alpha_1 < \beta$. Therefore, addition of players of type 1 leads to positive values for $\Delta_2(y_1, y_2)$ at lower values of α_2. In other words, there is a threshold τ such that for any $\tau < \alpha_2 < \frac{n_2^\beta - 1}{n_2 - 1}$ the social optimal solution includes all n_2 players of type 2 when they are considered together with players of another type, i.e., $y_i^o > y_i^o(0)$. From the proof of Proposition 1, we can conclude that if

$$\tau < \alpha_2 < \frac{n_1^\beta - 1}{n_1 - 1}$$

the social optimal solution includes all players of both types, i.e., $y_2^o = n_2$, while myopic players of type 2 do not join the coalition. i.e., $y_2^* = 0$.

When players are forward looking, without loss of generality we assume $\alpha_2 > \alpha_1$. For any given y_2^* we have $g_1(y_1 + y_2^*) = \alpha_1 - \beta(y_1 + y_2^*)^{\beta - 1}$. Therefore, at $y_1 = 0$ we have

$$g_1^{'}(y_1 + y_2^*) = \alpha_1 - \beta {y_2^*}^{\beta - 1}$$

Therefore, when $\beta < 1$, the function $g_1(y_1 + y_2^*)$ is either increasing convex for all values of y_1 or it starts decreasing convex and later changes to increasing convex. Therefore, as long as $g_1(n_1 + y_2^*) > 0$ we have $y_1^* = n_1$. We have

$$g_1(n_1 + y_2^*) > 0 \Rightarrow \alpha_1 > \frac{(n_1 + y_2^*)^\beta - 1}{n_1 + y_2^* - 1}$$

And similarly for α_2 at (n_1, y_2). Therefore we have

$$\begin{cases} y_1^* = 0, y_2^* = 0 & \text{if } \alpha_2 < \dfrac{n_2^\beta - 1}{n_2 - 1} \\ y_1^* = 0, y_2^* = n_2 & \text{if } \alpha_2 > \dfrac{n_2^\beta - 1}{n_2 - 1} > \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + n_2 - 1} > \alpha_1 \\ y_1^* = n_1, y_2^* = n_2 & \text{if } \alpha_2 > \alpha_1 > \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + n_2 - 1} \end{cases}$$

The social optimal solution includes all n_i players of type i if $\Delta_i(n_1, n_2) > 0$. We note that $\Delta_i(n_1, n_2) > 0$ for $i = 1, 2$ at $\alpha_1 = \alpha_2 = \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + n_2 - 1}$. Therefore, and given that $\dfrac{\partial \Delta_i(y_1, y_2)}{\partial \alpha_i} > 0$ the social optimal coalition includes all $n_1 + n_2$ players also at lower values of α_i, $\forall i = 1, 2$. In other words, we have a threshold $\tau < \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + n_2 - 1}$ such that if $\tau < \alpha_i < \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + n_2 - 1}$ we have $y_i^o = n_i$ and $y_i^* = 0$ for $i = 1, 2$.

Proposition 3

When $\beta > 1$, if $\alpha_k < \beta$, we have $g_k^{'}(1) < 0$ and $g_k(y_k)$ is decreasing concave for all $y_k > 1$ and therefore HOs of type k do not join any coalition.

On the other hand, if (H.2) holds, i.e., $\alpha_k > \beta$, then $g_k(y_k)$ is concave, initially increasing at $y_k = 1$ and eventually decreasing to $-\infty$. Therefore, $g_k(y_k)$ has two roots on $[1, \infty)$ at $y_k = 1$ and $y_k = y_k^* > 1$. Thus, if $y_k^* < 2$, or equivalently if $g_k(2) < 0$, the only equilibrium is operating alone, i.e., myopic and forward looking players will decide to not join the coalition. We know that $g_k(2) < 0$ when $\alpha_k < 2^\beta - 1$.

When $\beta > 1$ and $\alpha_k < \beta < 2^\beta - 1$, social welfare function is decreasing in y_k at any $y_k + y_{3-k} \geq 1$. Therefore, we have $y_k^o = y_k^o(0) = 0$ for $k = 1, 2$. If $\beta < \alpha_k < 2^\beta - 1$, we have $\nabla \hat{U}(y_1, y_2) < \mathbf{0}$ for any coalition where $y_1 + y_2 \geq 2$. Therefore, it is the social optimal that HOs of type k do not join a coalition.

Proposition 4

Let us denote marginal benefits of coordination for small and large HOs as α_S and α_L, respectively, where $\alpha_S < \alpha_L$. If small HOs are first in the sequence (i.e., the sequence is in ascending order of α_k), y_{SA}^* small HOs join the coalition such that

$$y_{SA}^* = \max\{y : \alpha_S y - y^\beta - \alpha_S + 1 \geq 0\}. \tag{H.4}$$

Then, among large HOs that are next in the sequence, knowing that y^*_{SA} players are in the coalition, a number equal to y^*_{LA} will join such that

$$y^*_{LA} = \max\{y : \alpha_L(y^*_{SA} + y) - (y^*_{SA} + y)^\beta - \alpha_L + 1 \geq 0\}. \quad \text{(H.5)}$$

If the sequence is reversed, i.e., if large HOs precede, then y^*_{LD} of them join such that

$$y^*_{LD} = \max\{y : \alpha_L y - y^\beta - \alpha_L + 1 \geq 0\}. \quad \text{(H.6)}$$

Then, small HOs solve the following problem:

$$y^*_{SD} = \max\{y : \alpha_S(y + y^*_{LD}) - (y_1 + y^*_{LD})^\beta - \alpha_S + 1 \geq 0\}. \quad \text{(H.7)}$$

From (H.5) and (H.6), we have $y^*_{LD} = y^*_{SA} + y^*_{LA}$. Therefore, $y^*_{LD} \geq y^*_{LA}$. Also, from (H.4) and (H.7), we have $y^*_{SD} \leq y^*_{SA}$.

Proposition 5

When $\beta > 1$ and $\alpha_k < 2^\beta - 1$, as shown in Proposition 3 the equilibrium and social optimal solutions include no HOs of type k.

We now first consider the case that only type 2 HOs are considered. (The proof for type 1 HOs is similar.) If $\alpha_2 \geq 2^\beta - 1$, we have two possibilities. If

$$1 < \frac{\beta + 1}{2} < \frac{\alpha_2}{\beta} \quad \text{(H.8)}$$

then $\hat{U}''_{y_2}(0, 1) > 0$, i.e., social welfare is initially convex increasing, and at

$$y_2 = y_2' = \left(\frac{2\alpha_2}{\beta(\beta + 1)}\right)^{\frac{1}{\beta - 1}}$$

we have $\hat{U}''_{y_2}(0, y_2) = 0$ and the function shifts from convex increasing to concave increasing. Furthermore,

$$\hat{U}'_{y_2}(0, y_2) = 2\beta\Big(\frac{\alpha_2}{\beta}y - \frac{\beta + 1}{2\beta}y^\beta - \frac{\alpha_2 - 1}{2\beta}) \Rightarrow \lim_{y \to \infty} U'_{y_2}(y) = -\infty$$

Therefore, the optimal coalition size is the unique stationary point on $(1, \infty)$, i.e., the optimal coalition size is the unique solution

$$y^o_2 = \{y : 2\alpha_2 y - (\beta + 1)y^\beta - \alpha_2 + 1 = 0, y > 1\} \quad \text{(H.9)}$$

On the other hand, if

$$1 < \frac{\alpha_2}{\beta} < \frac{\beta + 1}{2} \quad \text{(H.10)}$$

then $\hat{U}''_{y_2}(0, y_2) < 0$ for all $y_2 > 1$, and thus the optimal coalition size is the unique stationary point on $(1, \infty)$, i.e., the optimal coalition size is the unique solution (H.9).

Note that when $\beta > 1$ and $\frac{\alpha_2}{\beta} < \frac{\beta+1}{2}$, we have

$$\hat{U}'_{y_2}(0,2) = 3\alpha_2 + 1 - (\beta+1)2^{\beta} < 0$$

Therefore, since $\hat{U}'_{y_2}(0,1) > 0$ and $\hat{U}'_{y_2}(0,2) < 0$, the unique stationary point is at a point where $1 < y_2^o < 2$. Therefore, given the integer requirement for y_2^o, the solution is a coalition of maximum 2 HOs, which occurs only when $\alpha_2 \geq 2^{\beta} - 1$. This condition holds only when $\beta < 2$ and $\frac{\alpha_2}{\beta}$ is very close to $\frac{\beta+1}{2}$.

Further, we have

$$\hat{U}(0, y_2^*) = u_0 + y^* g_2(0, y_2^*) = u_0,$$

i.e., social welfare at the equilibrium is equal to social welfare of no coalition (coexistence). Therefore, if $\alpha_2 \geq 2^{\beta} - 1$, i.e., if the social optimal and equilibrium coalition sizes are greater than 1, concavity of $g_2(0, y_2)$ means

$$\begin{cases} \hat{U}(0, y_2) < u_0 & \forall y_2 > y_2^* \\ \hat{U}(0, y_2) > u_0 & \forall y_2 \in (1, y_2^*) \end{cases}$$

which implies that the equilibrium coalition size is greater than the social optimal coalition size, i.e.,

$$y_2^o < y_2^* \tag{H.11}$$

If $n_2 < y_2^*$, the game has two Nash equilibria: (i) no coalition, (ii) a coalition of size n_2. We note that since $g_2(0, y_2)$ is increasing and concave, $g_2(0, n_2) > g_2(0, 1) = u_0$. Therefore, the equilibrium of n_2 players is utility-dominant. If we also have $n_2 < y_2^o$, then $y_2^* = y_2^o = n_2$. Otherwise, if $y_2^o < n_2$, then the social optimal coalition includes $y_2^o < y_2^* = n_2$ players. If $y_2^* \leq n_2$, the equilibrium coalition includes $\lfloor y^* \rfloor$ HOs. As shown in (H.11), $y_2^o < y_2^*$.

We now consider both types of players. If $\beta > 1$ and $\alpha_1 > \beta$, $g_1'(1) > 0$, $g_1(y_1)$ is concave and initially increasing at $y_1 = 1$ and eventually decreasing to $-\infty$. Therefore, there exists a $y_1^* > 1$ where $g_1(y_1^*) = 0$. If $n_1 < y_1^*$ then all n_1 players of type 1 join the coalition. Otherwise, the first randomly assigned $\lfloor y_1^* \rfloor$ players of type 1 join the coalition and the remaining will work independently.

First, we consider the case that $n_1 > y_1^*$. Note that (H.1) holds only if $\alpha_2 > \alpha_1$. If $\alpha_2 < \alpha_1$ only $\lfloor y_1^* \rfloor$ players join the coalition. As shown above, the social optimal coalition consists of y_1^o players of type 1 only and the social optimal coalition includes fewer number of players, i.e., $y_1^o < y_1^*$.

If $\alpha_2 > \alpha_1$, players form a coalition including y_1^* and y_2^* players of types 1 and 2, respectively. At this point we have $g_2'(y_1^* + y_2^*) < 0$. We also have

$$\nabla \hat{U}(y_1^*, y_2^*) = \begin{pmatrix} 2\alpha_1 y_1^* + (\alpha_1+\alpha_2)y_2^* - (\beta+1)(y_1^*+y_2^*)^{\beta} - \alpha_1 + 1 \\ 2\alpha_2 y_2^* + (\alpha_1+\alpha_2)y_1^* - (\beta+1)(y_1^*+y_2^*)^{\beta} - \alpha_2 + 1 \end{pmatrix}$$

We know that

$$g_2(y_1^* + y_2^*) = \alpha_2(y_1^* + y_2^*) - (y_1^* + y_2^*)^\beta + \alpha_2 - 1 = 0. \tag{H.12}$$

Therefore, we have

$$\hat{U}'_{y_1}(y_1^*, y_2^*) = 2\alpha_1 y_1^* + (\alpha_1 + \alpha_2)y_2^* - \alpha_2(y_1^* + y_2^*) - \beta(y_1^* + y_2^*)^\beta - (\alpha_1 + \alpha_2) + 2$$

Since $g_2'(y_1^* + y_2^*) = \alpha_2 - \beta(y_1^* + y_2^*)^{\beta-1} < 0$, we have

$$\hat{U}'_{y_1}(y_1^*, y_2^*) < 2(\alpha_1 - \alpha_2)y_1^* + (\alpha_1 - \alpha_2)y_2^* + 2 - (\alpha_1 + \alpha_2)$$

When $\alpha_2 > \alpha_1 > \beta > 1$, all of the terms on the right hand side are negative. Therefore, $\hat{U}'_{y_1}(y_1^*, y_2^*) < 0$.

Similarly, we have

$$\begin{aligned}\hat{U}'_{y_2}(y_1^*, y_2^*) &= \alpha_1 y_1^* + \alpha_2 y_2^* - \beta(y_1^* + y_2^*)^\beta - (\alpha_1 + \alpha_2) + 2\\ &< (\alpha_1 - \alpha_2)y_1^* + 2 - (\alpha_1 + \alpha_2).\end{aligned}$$

Thus, when $\alpha_2 > \alpha_1$ and $\beta > 1$, $\hat{U}_2'(y_1^*, y_2^*) < 0$.

Further, since $g_1'(y_1^*) < 0$ and $g_1'(y)$ is decreasing in y, we have $g_1'(y_1^* + y_2^*) = \alpha_1 - \beta(y_1^* + y_2^*)^{\beta-1} < 0$. Therefore,

$$\hat{U}''_{y_1}(y_1^*, y_2^*) < 2\beta\Big((1 - \frac{\beta+1}{2})(y_1^* + y_2^*)^{\beta-1}\Big).$$

When $\beta > 1$, we have $\hat{U}''_{y_1}(y_1^*, y_2^*) < 0$. Similarly, since $g_2'(y_1^* + y_2^*) < 0$, we have $\hat{U}''_{y_2}(y_1^*, y_2^*) < 0$. Also, as $\hat{U}''_{y_1y_2}(y_1^*, y_2^*) = \frac{1}{2}(\hat{U}''_{y_1}(y_1^*, y_2^*) + \hat{U}''_{y_2}(y_1^*, y_2^*))$, we also have $\hat{U}''_{y_1y_2}(y_1^*, y_2^*) < 0$. Therefore, the social welfare function is decreasing at any point (y_1, y_2) where $y_1 \geq y_1^*$ and $y_2 \geq y_2^*$. Therefore, social welfare is maximized with fewer number of players in the coalition, i.e., $y_1^o + y_2^o < y_1^* + y_2^*$.

If $n_1 < y_1^*$, all n_1 players of type 1 join the coalition. If $n_1 > \left(\frac{\alpha_1}{\beta}\right)^{\frac{1}{\beta-1}}$ then $g_1'(n_1) = \alpha_1 - \beta {n_1}^{\beta-1} < 0$. Therefore, we have $\frac{\alpha_2}{\beta} > {n_1}^{\beta-1}$ only if $\alpha_2 > \alpha_1$. We therefore have $y_1^o + y_2^o < n_1 + y_2^*$. The proof follows the case of $n_1 > y_1^*$.

If $n_1 < y_1^*$ and $n_1 < \left(\frac{\alpha_1}{\beta}\right)^{\frac{1}{\beta-1}}$, it is possible to have $\frac{\alpha_2}{\beta} > {n_1}^{\beta-1}$ for some values of α_2 where $\alpha_2 < \alpha_1$. In that case, from the case of one type of players, we know that the social optimal solution is a coalition of y_1^o HOs of type 1 if $y_1^o < n_1$. Therefore, the optimal solution includes fewer number of HOs, i.e., $y_1^o < n_1 + y_2^*$. If $y_1^o > n_1$, then the social optimal coalition is either a coalition of y_1^o HOs of type 1 or a total of $y_2^o + n_1 < y_1^o$ HOs of the two types. From the case of single player type we know that $y_1^o < y_1^*$. Therefore, the social optimal coalition is always smaller than or equal to the equilibrium outcome.

Proposition 6

Equilibrium

When $\beta < 1$ and players are myopic, similar to the proof of Proposition 1, we have $y_1^* = n_1$ if $\alpha_1 > 2^\beta - 1$. Then if $g_{D2}(1, n_1) > 0$, n_2 players of type 2 will also join the coalition. We have

$$g_{D2}(1, n_1) > 0 \Rightarrow \alpha_2 > \frac{(\rho n_1 + 1)^\beta - 1}{n_1}$$

Therefore, as the system gets decentralized, i.e., as ρ decreases, the minimum threshold above which players of type 2 will join the coalition also decreases. Therefore, for $\rho < 1$, when we have $\frac{(\rho n_1 + 1)^\beta - 1}{n_1} < \alpha_2 < \frac{n_1^\beta - 1}{n_1 - 1}$ all players of type 2 will join the coalition while they would not join in a centralized model.

When $\beta < 1$ and players are forward-looking, the proof follows that of Proposition 2. Without loss of generality, we assume $\alpha_2 > \alpha_1$. We have $y_1^* = n_1$ as long as $g_{D1}(n_1, y_2^*) > 0$. Furthermore,

$$g_{D1}(n_1, y_2^*) > 0 \Rightarrow \alpha_1 > \frac{(n_1 + \rho y_2^*)^\beta - 1}{n_1 + y_2^* - 1}$$

Therefore, we have:

$$\begin{cases} y_1^* = 0, y_2^* = 0 & \text{if } \alpha_2 < \dfrac{n_2^\beta - 1}{n_2 - 1} \\ y_1^* = 0, y_2^* = n_2 & \text{if } \alpha_2 > \dfrac{n_2^\beta - 1}{n_2 - 1} > \dfrac{(n_1 + \rho n_2)^\beta - 1}{n_1 + n_2 - 1} > \alpha_1 \\ y_1^* = n_1, y_2^* = n_2 & \text{if } \alpha_2 > \alpha_1 > \dfrac{(n_1 + n_2)^\beta - 1}{n_1 + \rho n_2 - 1} \end{cases}$$

Note that the thresholds decrease as ρ decreases, i.e., when the system gets decentralized. Therefore, HOs join at lower levels of α_1 and α_2 as compared to a centralized system.

When $\beta > 1$ and players are myopic, $y_1^* > 0$ players of type 1 join as long as $\alpha_1 > \beta$. We note that

$$\frac{\partial g_{Dk}(y_k, y_{3-k})}{\partial \rho} = -y_{3-k}\beta(y_k + \rho y_{3-k})^{\beta-1} < 0 \tag{H.13}$$

As ρ decreases, the value of $g_{Dk}(y_k, y_{3-k})$ increases at any given point. Therefore, the value of y^* increases as the system is decentralized.

Then, $y_2^* > 0$ will also join if $g_{D2}(0, y_1^*) > 0$. We have

$$g_{D2}(0, y_1^*) = g_{D1}(y_1^*, 0) + (\alpha_2 - \alpha_1)(y_1^* - 1) + (1 - \rho^\beta)y_1^{*\beta}$$

Noting that $g_{D1}(y_1^*, 0) = 0$, as ρ decreases, $g_{D2}(0, y_1^*) > 0$ at lower values of α_2. From (H.13) we know that the value of $g_{D2}(y_1^*, y_2)$ increases as ρ is decreased. Further, at any y_2 we have

$$\frac{\partial^2 g_{D2}(y_1^*, y_2)}{\partial\rho\partial y_1^*} = -\beta(y_2 + \rho y_1^*)^{\beta-1} - y_1^*\beta(\beta-1)\rho(y_2 + \rho y_1^*)^{\beta-2} < 0$$

Therefore, the increase in $g_{D2}(y_1^*, y_2)$ due to decentralization is higher at higher values of y_1^*.

Social optimal

When $\beta < 1$, following the proof of Proposition 2, we define $\Delta_1(y_1, y_2) = \hat{U}(y_1, y_2) - \hat{U}(0, y_2)$. We have

$$\Delta_1(y_1, y_2) = \alpha_1 y_1^2 + y_2^{\beta+1}(1-\alpha_1)y_1 + (\alpha_1 + \alpha_2)y_1 y_2 - y_1(y_1 + \rho y_2)^\beta - y_2(y_2 + \rho y_1)^\beta$$

Note that

$$\frac{\partial\Delta_1(y_1, y_2)}{\partial\rho} = -y_1 y_2\Big((y_1 + \rho y_2)^{\beta-1} + (y_2 + \rho y_1)^{\beta-1}\Big) < 0$$

Therefore, as ρ decreases, we have $\Delta_1(y_1, y_2) > 0$ and thus $y_1^o = n_1$ at lower values of α_1. The same holds for $\Delta_2(y_1, y_2)$ and α_2.

At any given point (y_1, y_2) we have

$$\frac{\partial\hat{U}_D(y_1, y_2)}{\partial\rho} = -y_1 y_2 \beta\Big((y_1 + \rho y_2)^{\beta-1} + (y_2 + \rho y_1)^{\beta-1}\Big) < 0.$$

In other words, social welfare at any point increases as the system gets decentralized. Further, for $k = 1, 2$ we have

$$\begin{aligned}
\frac{\partial^2\hat{U}_D(y_k, y_{3-k})}{\partial y_k\partial\rho} &= -\, y_{3-k}\beta(y_k + \rho y_{3-k})^{\beta-1} - y_{3-k}y_k\beta(\beta-1)(y_k + \rho y_{3-k})^{\beta-2} \\
&\quad - y_{3-k}\beta(y_{3-k} + \rho y_k)^{\beta-1} - y_{3-k}y_k\beta\rho(y_{3-k} + \rho y_k)^{\beta-2} < 0 \qquad \text{(H.14)} \\
\frac{\partial^3\hat{U}_D(y_k, y_{3-k})}{\partial y_k\partial y_{3-k}\partial\rho} &= -\,\beta\Big(\beta + (\beta-1)^2\rho^{\beta-2} + \beta\rho^{\beta-1}\Big) < 0
\end{aligned}$$

Therefore, for any $\beta > 0$, the slope of social welfare function increases at any point when ρ is decreased. Thus, as the system gets decentralized, the optimal coalition size and the optimal social welfare both increase.

Proposition 7

Low time burden ($\beta < 1$)

We define α_k^o and α_k^* as the value of α_k above which the social optimal and the equilibrium includes n_k players of type k. We have

$$\alpha_k^o = \frac{n_k(n_k + \rho n_{3-k})^\beta + n_{3-k}(n_{3-k} + \rho n_k)^\beta - \alpha_{3-k} n_k n_{3-k} - n_{3-k}^{\beta+1}}{n_k^2 + n_k n_{3-k} - n_k},$$
$$\alpha_k^* = \frac{(n_k + \rho n_{3-k})^\beta - 1}{n_k + n_{3-k} - 1}.$$

Further,

$$\frac{\partial \alpha_k^o}{\partial \rho} = \frac{n_{3-k\beta}}{n_k + n_{3-k} - 1}\Big((n_k + \rho n_{3-k})^{\beta-1} + (n_{3-k} + \rho n_k)^{\beta-1}\Big)\frac{\partial \alpha_k^*}{\partial \rho} = \frac{n_{3-k}\beta(n_k + \rho n_{3-k})^{\beta-1} - 1}{n_k + n_{3-k} - 1}.$$

We have $\dfrac{\partial \alpha_k^o}{\partial \rho} > \dfrac{\partial \alpha_k^*}{\partial \rho}$. Therefore, as ρ is decreased, the range of α_k for which the social optimal includes n_k players increases more than the range for which the equilibrium coalition includes n_k players. In other words, when the system gets decentralized, there is a range of α_k for which the social optimal includes all n_k HOs of type k, while the equilibrium remains the same as a centralized coalition where players of type k do not join.

High time burden ($\beta > 1$)

From Proposition 5 we know that when $\rho = 1$, we have $\dfrac{\partial \hat{U}(y_1^*, y_2^*)}{\partial y_k} < 0$ for $k = 1, 2$. From Proposition 6, we know that y_k^* increases or remains the same as the system gets decentralized. Note that at y_k^* we have $g_{Dk}(y_1^*, y_2^*) = 0$ and at y_k^o we have $\dfrac{\partial \hat{U}_D(y_1^o, y_2^o)}{\partial y_k} = 0$. From (H.13) and (H.14) we have $\dfrac{\partial^2 \hat{U}_D(y_k, y_{3-k})}{\partial y_k \partial \rho} < \dfrac{\partial g_{Dk}(y_k, y_{3-k})}{\partial \rho} < 0$. Therefore, for a certain decrease in ρ, the optimal coalition size increases by a larger value than the equilibrium coalition size increases. Therefore, when the system gets decentralized the difference between the optimal social welfare and the value of social welfare at the equilibrium decreases.

Note that we have

$$\frac{\partial \hat{U}(y_1, y_2)}{\partial y_k} = (2y_k + y_{3-k} - 1)\alpha_k - (y_k + \rho y_{3-k})^\beta - \beta\Big(y_k(y_k + \rho y_{3-k})^{\beta-1} + \rho y_{3-k}(y_{3-k} + \rho y_k)^{\beta-1}\Big) + \alpha_{3-k} y_{3-k} + 1$$

Therefore,

$$\lim_{\rho \to 0^+} \frac{\partial \hat{U}(y_1, y_2)}{\partial y_k} = (2y_k + y_{3-k} - 1)\alpha_k - (\beta + 1)y_k^\beta + \alpha_{3-k} y_{3-k} + 1$$

Note that

$$\lim_{\rho \to 0^+} g_{Dk}(y_k^*, y_{3-k}^*) = (2y_k + y_{3-k} - 1)\alpha_k - y_k^\beta + 1 = 0$$

Therefore, we have

$$\lim_{\rho \to 0^+} \frac{\partial \hat{U}(y_1^*, y_2^*)}{\partial y_k} = \alpha_{3-k} y_{3-k}^* - (\beta {y_k^*}^\beta - \alpha_k y_k^*).$$

At high levels of α_{3-k}, it is possible to have $y_k^* < y_k^o$ if the level of decentralization is very high. In other words, under such circumstances, there is a $0 < \rho < 1$ for which we have $y_k^* = y_k^o$.

APPENDIX I

PERMISSIONS

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