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Does governance ease the overhead squeeze experienced by nonprofits?

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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 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, although PSR still remains a key driver. Moreover, our findings show that better governance is associated with a 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.

KEYWORDS
nonprofits, social services charities, program spending ratio, governance quality

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) (Internal Revenue Service, 2022). Most charitable giving comes from individuals (e.g., 69% in 2020), followed by foundations and corporations (Giving USA, 2019). The growth of the nonprofit sector is considered beneficial for society but increases competition among nonprofits (Berenguer & Shen, 2020; Castaneda et al., 2008). 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 a high risk of failure, and so securing donations is an important goal in their strategies (Calabrese, 2013).

Traditionally, donations are linked to the *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 United States (Lecy & Searing, 2015) and Germany (Schubert & Boenigk, 2019). Industry practitioners, however, believe that too much emphasis on

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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 & 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 (Becker, 2018; Devalkar et al., 2017). 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 program-related data is a solution to information asymmetry that should increase donors' trust (Saxton & 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 | Program spending ratio

Studies show that donors support nonprofits with higher PSR (Gneezy et al., 2014; Yan & 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 (Gneezy et al., 2014; Kinsbergen & Tolsma, 2013).

On the other hand, the focus on PSR has been criticized for a number of reasons. First, it reflects neither a nonprofit's actual performance nor the real social value of its missions (Coupet & Berrett, 2019; Eftekhar et al., 2017; Glassman & Spahn, 2012). Second, achieving a 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 3 months of expenses, and about 30% had no operating reserves at all (Blackwood & Pollak, 2009). Therefore, overemphasizing PSR and cutting overheads provide counterproductive incentives in the long term. It can inhibit program outcomes (Altamimi & Liu, 2021) and the sustainability of nonprofits (Park & Matkin, 2021) and impede 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).

1.2 | 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. 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; Garven et al., 2018; Newton, 2015). 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 (Gneezy et al., 2014; Kinsbergen & Tolsma, 2013), 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 the approval of a governing body to ensure comparability with similar nonprofits.

1.3 | An operations management perspective

A fundamental difference between the operations of 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 to 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 (Eftekhar et al., 2022; Keshvari Fard et al., 2019). Accordingly, donation income is the critical resource for nonprofits, and it influences the viability, sustainability, efficiency, and scalability of nonprofit operations (Berenguer & Shen, 2020; Lewis, 2004). 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 & Shen, 2020), and force them to make myopic decisions (Arya & 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 operations management literature offers insights into how to optimally allocate budgets in distribution and last-mile delivery in humanitarian settings (Eftekhar et al., 2022; Vanajakumari et al., 2016), this paper highlights the role of budget allocation decisions on nonprofits' capacity and income.

Donors also have a role in monitoring nonprofit operations, although they are based on inaccurate measures (Berenguer & Shen, 2020). In that regard, information disclosure regarding governance practices allows donors to better monitor nonprofits (Molk & Sokol, 2021; Zhuang et al., 2014). Potential managerial misconduct and the use of nonprofit funds for purposes other than the organizations' missions are among the governance issues that have adverse impacts on their operations (Molk & Sokol, 2021). Further, better governance is associated with higher efficiency in operations (Newton, 2015). For instance, nonprofit governing models 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.

1.4 | Contribution of this paper

In this paper, we reexamine 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 16 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, for example, 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 & 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 the publicly available information (Andreoni & 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 on nonprofits (Balsam & 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 on 38,226 U.S.-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 to 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 distinguish 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 a lower likelihood of reporting zero fundraising expenses, pointing to at least one mechanism through which governance reduces the pressure to report an 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) are among the very few studies that provide 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 the disclosure of governance quality information was the result of a sector-wide policy, highlighting the role of policymakers in helping nonprofits to avoid the starvation cycle.

Further, the existing evidence on the role of PSR is typically based on experimental studies (Bekkers & 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 have experimentally examined 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 & Horn, 2020) on donors' attitudes towards PSR, and the impact of governance and accountability and their relationship with PSR and donations have largely been overlooked (Dang & 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 a lack of incentives and disciplining devices (Bolton & 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 the 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 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 have increased 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 a lower likelihood of reporting zero fundraising.

2 | RESEARCH SETTING AND DATA

The dataset for this study includes information on 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 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 from 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 & 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 nonpositive total expenses, nonpositive assets, negative program expenses, program expenses more than total expenses, negative fundraising expenses, nonpositive 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 comprises 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.

3 | METHODS

To examine the role of PSR and governance in driving donations, we consider Equation (1),

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

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 & Gras, 2019), mitigates skewness and heteroscedasticity 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 16 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 into four subindices; governing body, governing policies, compensation policies, and accountability. For each organization-year observation, each subindex score is calculated as the ratio between the sum of the component scores of that observation and the total possible score in that subindex. 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 three possible points in the accountability subindex, that is, a score of 100. If there was no oversight committee, all else equal, the organization would have a score of 67 in this subindex. Governance is then calculated as the average score of the nonprofit in that year in these four subindices and ranges between zero and 100. For example, if an organization receives 80%, 80%, 60%, and 60% of the possible scores in the four subindices in a given year, its governance score equals 70. (See Supporting Information 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 & Tolsma, 2013). Second, we control for the effect of *government grants* as their 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, that is, a crowd-out effect (Andreoni & Payne, 2003). Simultaneously, they might consider government grants as an indicator of the organizations' capabilities or capacity, that is, a crowd-in effect (Andreoni & Payne, 2011). Third, a nonprofit's financial capacity, including revenue from services and investments, ensures the continuity of its operations and so it affects public donations (Yan & Sloan, 2016). Consequently, we consider the natural logarithm of organizations' *own income* as a control variable assuming that when a nonprofit has a 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 (Okten & Weisbrod, 2000). Because donors differ in the type of charitable programs they prefer to support (Andreoni & Payne, 2003; Rose-Ackerman, 1982), 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 & 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 a higher HHI indicates a higher concentration (an HHI equal to 1 shows a perfect concentration). Further, donors prefer to have higher control over their contributions. Hence, earmarking is associated with higher donation income (Nunnenkamp & 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 the potential for misreporting and result in more realistic reported financials (Garven et al., 2018; R. J. Yetman & M. Yetman, 2011). 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 (2).

$$
\begin{aligned}
PSR_{i(t-1)} = {} & \beta_1 Governance_{i(t-1)} + \beta_2 \log(Assets_{i(t-1)}) \\
& + \beta_3 \log(GovernmentGrants_{i(t-1)}) \\
& + \beta_4 \log(OwnIncome_{i(t-1)}) \\
& + \beta_5 \log(Earmarked_{i(t-1)}) \\
& + \beta_6 ProgramConcentration_{i(t-1)} \\
& + \beta_7 ZeroFundraising_{i(t-1)} \\
& + \beta_8 LiabilityToAsset_{i(t-1)} + \phi_{(t-1)} + \gamma_i + \epsilon_{i(t-1)}.
\end{aligned} \tag{2}
$$

Following the literature, we use two additional control variables in Equation (2): we add the *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 (Harris et al., 2015; Krishnan et al., 2006; Newton, 2015). Tables 1 and 2 provide descriptive statistics and correlations of the variables used in the estimations, respectively. Supporting Information Appendix B provides summary statistics of raw values before log transformation.

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

TABLE 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

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

TABLE 2 Correlations of variables used in the 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

our main variables. We do so by using *intraclass correlation coefficients* (ICCs) that show the between-organization variance in 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 by estimating mixed-effects within-between specifications of our equations. These initial results, presented in Table C.1 in Supporting Information Appendix C, are not corrected for endogeneity.

3.2 | Fixed-effect IV estimation

A mixed-effect estimation approach cannot explicitly model endogeneity. Estimates may therefore be biased due to the existence of omitted variables. In our setting, there are two potential sources of endogeneity. First, in Equation (1), we are concerned about endogeneity of *fundraising investment* because unobserved variables might influence both a nonprofit's fundraising investment and its donation income. For example, a large-scale disaster can increase giving and may decrease or increase the need for fundraising (Andreoni & Payne, 2011). Although the direction of this impact is not clear, it can bias our estimates. Second, in Equation (2), *governance* might be the source of endogeneity. Unobserved characteristics could cause a 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 that any confounding variable is similarly correlated with the control variables (Larcker & 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 the 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 the 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. The 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 & 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 that 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 the governance quality of other organizations. (For details, see Supporting Information 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 generalized method of moments (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) and that for endogeneity of $Governance_{i(t-1)}$ in Equation (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 & Peixe, 2003). As we estimate Equation (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 that our IVs are valid (Anderson & Rubin, 1949; Kleibergen & Paap, 2006; Sanderson & Windmeijer, 2016). Specifically, when we estimate Equation (1) treating $\log(Fundraising_{it})$ and $Governance_{i(t-1)}$

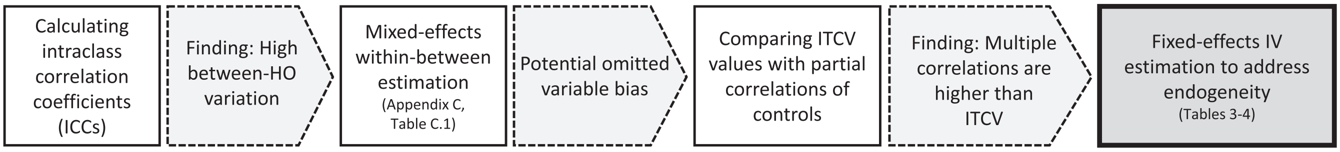

FIGURE 1 Summary of estimation strategy: We started with a mixed-effects method, but then continued our analysis based on a fixed-effects IV estimation

as endogenous, the Sanderson–Windmeijer multivariate F statistic equals 27.97 and 27.66 for these two variables, respectively, and the Kleibergen–Paap rank (rk) LM statistic equals $\chi^2(1) = 25.38$, rejecting the null hypothesis of underidentification 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 & Rubin, 1949). Similarly, the Kleibergen–Paap rk Wald F statistic equals 12.67, which indicates that weak identification is not a concern (Stock & Yogo, 2005). Similarly, as we estimate Equation (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 underidentification 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.

3.3 | Three-stage least square estimation procedure

Our full model is a system of two equations in which 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 (Greene, 2012; Wooldridge, 2010). 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 squares (3SLS) is a more efficient procedure than the 2SLS, which neglects the correlation between the two equations (Zellner & Theil, 1992). Therefore, we estimate the system of Equations (1) and (2) using 3SLS, instrumenting fundraising expenses and governance quality using the abovementioned instruments. Figure 1 summarizes the analytical approach and reasons why we chose this approach.

4 | RESULTS, EXTENSION, AND ROBUSTNESS

4.1 | Main results

Our results, summarized in Table 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 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 1 percentage point increase in PSR, on average, leads to a 16.94%[1] increase in donation income (at $p < 0.001$), underlining the importance of PSR. The total effect of governance, reported in Table 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 a 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 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 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 a major driver of donations, verifying previous findings (e.g., Khanna & Sandler, 2000). Fundraising plays the same role for a nonprofit as advertising in the commercial sector (Okten & Weisbrod, 2000)

TABLE 3 3SLS estimation results of the full model

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	174,419	174,419
χ^2 test	414.9002 [$p < 0.001$]	2255.5088 [$p < 0.001$]

Note: Endogenous variables are $\log(Fundraising_{it})$ and $Governance_{i(t-1)}$; IVs are $\log(Occupancy_{it})$ and $GovernanceIV_{i(t-1)}$. Numbers in parentheses show standard deviations.

TABLE 4 Total effects of $Governance_{i(t-1)}$ and control variables

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) [$p = 0.848$]

Note: Numbers in parentheses show standard deviations.

TABLE 5 Coefficients on instruments from the 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 [$p < 0.001$]

and is nonprofits' predominant strategy to increase donations (Eftekhar et al., 2017; Thornton, 2006).

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 & 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 that would further restrict the use of their assets. Moreover, donors who prefer to have control over their contributions may perceive that a nonprofit with more earmarked assets is less likely to spend their contributions on 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 for organizations that specialize in specific programs (Bilodeau & Slivinski, 1997; Penna, 2011). However, as the second column of Table 3 shows, on average, nonprofits' PSR falls as they focus on fewer programs. Put differently, the 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.

4.2 | First-stage results: The effects of instruments

Table 5 reports the coefficients on instruments from the first-stage estimates. (Full first stage results are provided in Supporting Information 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*, that is, 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.

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 that 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 (3).

$$
\begin{aligned}
&ZeroFundraising_{it}\\
&\quad = \delta_0 + \sigma_1\overline{Governance_i} + \sigma_2\overline{\log(Assets_{it})_i}\\
&\qquad + \sigma_3\overline{\log(GovernmentGrants_{it})_i} + \sigma_4\overline{\log(OwnIncome_{it})_i}\\
&\qquad + \sigma_5\overline{\log(Earmarked_{it})_i} + \sigma_6\overline{ProgramConcentration_i}\\
&\qquad + \delta_1\left(Governance_{it} - \overline{Governance_i}\right)\\
&\qquad + \delta_2\left(\log(Assets_{it}) - \overline{\log(Assets_{it})_i}\right)\\
&\qquad + \delta_3\left(\log(GovernmentGrants_{it}) - \overline{\log(GovernmentGrants_{it})_i}\right)\\
&\qquad + \delta_4\left(\log(OwnIncome_{it}) - \overline{\log(OwnIncome_{it})_i}\right)\\
&\qquad + \delta_5\left(\log(Earmarked_{it}) - \overline{\log(Earmarked_{it})_i}\right)\\
&\qquad + \delta_6\left(ProgramConcentration_{it} - \overline{ProgramConcentration_i}\right)\\
&\qquad + \phi_t + \mu_{it}. \qquad (3)
\end{aligned}
$$

Coefficients σ_1 to σ_6 indicate the effects of nonprofit means, that is, between-nonprofit effects, and coefficients δ_1 to δ_6 show the effects of demeaned variables, that is, 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 is 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 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 & 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 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 6 are likely to be reliable.

Results indicate that better governance is significantly associated with a 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 1%, 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 1% 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 program concentration. 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

TABLE 6 Mixed-effects logistic regression estimation results

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	220,971	
Nonprofits	38,143	
Wald test	16,317.5919 [$p < 0.001$]	

Note: 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. Numbers in parentheses show standard deviations.

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 a 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 indicated in Figure 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 the availability of governance information in differentiating between organizations with reliable and unreliable reports.

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 & Payne, 2011). Third, 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 subsectors 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 the misspecification of one of the equations (Baltagi, 2005). Results of these tests, which indicate that our results are robust, are provided in Supporting Information Appendix E.

5 | CONCLUDING REMARKS

Results of this study reveal that the 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

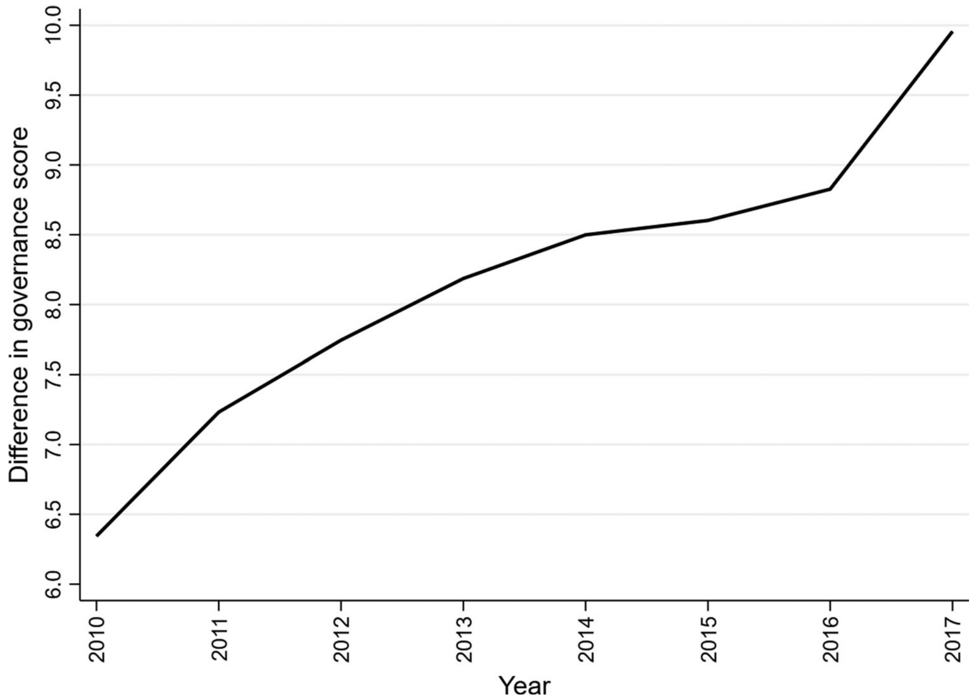

FIGURE 2 Difference between the average governance score of nonprofits with positive and zero reported fundraising investments

generally associated with lower PSR levels. While nonprofits' PSR has commonly been used as a proxy to determine their efficiency (Gneezy et al., 2014; Kinsbergen & Tolsma, 2013), 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 the average PSR; in the period since the IRS policy change that made it easier to communicate governance quality information, we find that this is no longer the case.

We also find evidence that better governance is associated with a lower potential for misreporting, suggesting a mechanism by which governance quality has eased the pressure on PSR. Results indicate the 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 the unavailability of data before 2008, we are unable to directly measure the impact of the IRS policy change. However, our results suggest that policymakers 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 dataset. 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 the PSR influences donations differently at different levels of governance quality. Our estimation settings do not allow rigorous analysis of this question. Specifically, we find it necessary to use IVs 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 on other insights.

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ENDNOTES

[1] $100 \times (\exp(0.1565) - 1) = 16.94\%$.
[2] $100 \times (1 - \exp(-0.0261)) = 2.58\%$.

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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