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RESEARCH ARTICLE

The role of operational expenditures and misalignments in fundraising for international humanitarian aid

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Abstract

Funding for international humanitarian aid falls far behind demand for disaster response, hampering the operations of international humanitarian organizations (IHOs). One remedy to close this gap is to increase the effectiveness of fundraising activities for IHOs. This remedy means spending as little as possible in fundraising activities but, at the same time, still receiving sufficient donations to implement disaster response programs in response to the needs that arise when disasters occur. We contribute to the literature by theoretically developing and estimating a conceptual framework that links donation behavior to the operations that IHOs aim to pursue; the framework incorporates operational costs communicated in appeals, fundraising efforts, and media attention. We argue that effects are not homogenous across disasters but that IHOs can leverage public attention and disaster and appeal characteristics, such as operational costs, to increase donations. We test the framework on a unique data set for disaster response programs operated by the International Federation of Red Cross and Red Crescent Societies (IFRC), covering 174 disasters to which the IFRC responded between 2010 and 2017.

KEYWORDS

donations, fundraising, humanitarian operations, IFRC, media attention, operational expenditures

1 | INTRODUCTION

When countries are struck by large disasters (e.g., the Ebola Virus Disease in 2014 in Guinea, the 2013 Haiyan typhoon in the Philippines, the 2010 earthquake in Haiti), international humanitarian organizations (IHOs) immediately respond to implement disaster response programs. These programs are usually multimillion-dollar programs (e.g., the International Federation of Red Cross and Red Crescent Societies – IFRC –, the organization that we study, asked donors for more than 85 million Swiss francs to respond to Typhoon Haiyan) and typically

cover a broad range of activities, including procurement, asset management, and logistics (van Wassenhove, 2006).

While large IHOs usually rely on special emergency funds to finance the initial disaster response, they immediately start raising donations to fund their relief operations, indicating that the IHOs reach out to many potential donors who might have only limited information about the relief programs that they are asked to donate to (Parsons, 2007); for example, potential donors might not be fully aware of the severity of the disaster, the required assistance, and the efficiency of the IHO. This limited information creates an information

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asymmetry problem (Akerlof, 1970; Parsons, 2007). Further, decision makers might lack the motivation, opportunity and ability to process all relevant information (Siemens, Roth, & Balasubramanian, 2008), for example, because they are approached by multiple IHOs for support of numerous programs. To address the information asymmetry and increase the motivation, opportunity and ability to process relevant information, many IHOs rely on fundraising activities. In these fundraising activities, defined as “the management of relationships between a charitable organization and its donor publics” (Kelly, 1998, p. 8), IHOs reach out to potential private and institutional donors¹ through advertising and other activities (e.g., electronic communication and phone calls). Hence, the goal of these activities is to raise donors' awareness of specific programs and to convince them to contribute to a given appeal. To this end, fundraising activities critically rely on budget appeals, which are documents that describe the impact of the disaster and the organization's plan to respond. Essentially, in these appeals, IHOs outline in detail the activities and the total amount of money required. IFRC, seeking full transparency, includes a detailed description of the categories that they are planning to spend the money on, such as operational expenditures (logistics, asset management, and procurement of food or shelters²) or other types of expenditures, such as support or indirect costs.

A key challenge that IHOs face is that demand for humanitarian aid exceeds the donations that they receive (Jahre & Heigh, 2008; Wakolbinger & Toyasaki, 2011), and this gap is growing (Stumpf, Guerrero-Garcia, Lamarche, Besiou, & Rafter, 2017). Further, the amount of donations that IHOs will receive to cover expenditures following their appeals is uncertain. Against this background, it is important to understand the impact of factors that affect the donations that IHOs receive, such as the fundraising and budget appeal characteristics (Burkart et al., 2016). The relevance of this challenge is underscored by the feedback that we have received in discussions with the IFRC management. Its managers have emphasized how the topic of this investigation is critical, given that there is an increasing push to become more strategic in their fundraising allocations: “it would be important for us to make more conscious decisions about fundraising”, stated an IFRC employee from the finance department during one of our visits.

A core tenet of this article is that the structure of the budget put forward in the appeal is a signal of the priorities pursued by the IHO in a given program. These priorities in turn might or might not be in line with the donors' preferences regarding the types of operations that should be run by IHOs, affecting the amount of donations that the IHO receives. For example, Eftekhar, Li, van Wassenhove, and Webster (2017) found that operational performance (the ratio of the total operational cost spent

on projects to the total expenditures) significantly affects institutional donations. At the same time, according to van Wassenhove (2006), donors seem to show a lack of understanding of the importance of specific operational activities, such as logistics or asset management, while in contrast, seeming to be eager to fund procurement-related activities. An empirical assessment of this conjecture, however, is still lacking, and Starr and van Wassenhove (2014) noted that the interplay between fundraising and operations represents an important research topic. Therefore, in our first research question, we consider the role of these three key operational expenditures included in budget appeals:

RQ1 *How do specific operational priorities and the corresponding expenditures affect donations to disaster response programs?*

IHOs, to efficiently allocate fundraising resources, must have reliable knowledge about what renders fundraising more or less effective, yet surprisingly little is known about the factors that affect the effectiveness of IHOs' fundraising activities (Burkart et al., 2016).

Previous research has focused primarily on the direct effects of fundraising activities (e.g., Eftekhar et al., 2017), but it has not systematically analyzed the factors moderating the effects of fundraising activities (i.e., making fundraising more or less effective). One critical process that coincides with IHOs' fundraising activities is the public attention that disasters receive. The literature has used the term “CNN disasters” for disasters that garner a large amount of media attention (Starr & van Wassenhove, 2014). This media attention increases donors' awareness (Besiou, Pedraza-Martinez, & van Wassenhove, 2014) and offers a large amount of visibility, which both donors (ECHO, 2009) and IHOs (Wakolbinger & Toyasaki, 2011) desire. While the literature has provided some evidence of a relationship between donations and public attention (Eftekhar et al., 2017; Waters & Tindall, 2011), it is unclear to what extent public attention actually helps IHOs in their fundraising activities, that is, whether IHOs can leverage public attention to maximize funding or to minimize fundraising efforts.

Similarly, previous research has not assessed how IHOs' operational priorities, which we described above, hurt or help fundraising effectiveness. This issue is particularly important against the background that better tailored fundraising policies could increase fundraising effectiveness without increasing costs (Ryzhov, Han, & Bradić, 2016), therefore allowing IHOs to allocate more resources on their operations. In this article, we study whether IHOs can leverage the interplay between fundraising and operational priorities to maximize donations. To the best of our knowledge, this topic has not been studied before, leading to our second research question:

RQ2 Which appeal (e.g., share of operational costs) and disaster characteristics (e.g., media attention) moderate the impacts of fundraising activities on donations to disaster response programs?

To complement our analysis of operational activities and the interplay with fundraising, we seek to understand how IHOs set their fundraising budgets. Previous research has rarely analyzed the potential factors that impact this decision, although it might inform us regarding the extent to which the behavior of the IHO and potential donors are aligned. Hence, our third research question is:

RQ3 To what extent do the operational priorities and the disaster characteristics affect the fundraising budget?

To address our research questions, we propose a conceptual framework of how operational expenditures impact fundraising and donations and how they interact with IHOs' fundraising activities and public attention. We focus on institutional donors, which make up approximately 75% of all donations to humanitarian aid worldwide (Global Humanitarian Assistance, 2017) and 99% of the donations of the IHO that is focal to our study. In addition, previous research has emphasized that institutional donors consider different factors when making their funding decisions (Eftekhar et al., 2017; Nunnenkamp & Öhler, 2012). We test our empirical framework using the case of the International Federation of Red Cross and Red Crescent Societies (IFRC).

Through this research, we contribute to the humanitarian operations literature by studying the impacts of three key operations types and their corresponding expenditures on donations and by assessing how fundraising expenditures, media attention, and the share of operational expenditures interact in their effects on donations. Additionally, we shed some light on how

IHOs set the levels of their fundraising efforts depending on the appeal and disaster characteristics.

The remainder of the article is organized as follows. We present our framework and hypotheses in Section 2. Section 3 describes the data and methodology used. Here, we also outline our identifying assumptions. We then present the results of our analysis in Section 4 and discuss our conclusions and directions for further research in Section 5.

2 | CONCEPTUAL FRAMEWORK

We propose a conceptual framework of how humanitarian organizations and donors respond when a disaster occurs. Figure 1 displays the framework, and it highlights two key processes (displayed in bold font in the framework) that involve IHOs and donors: (a) when a disaster occurs, IHOs decide on the composition of their budget appeals and, in particular, also their fundraising budgets; and (b) in response to these fundraising activities, donors decide whether and to what extent to support a given disaster response program.

This article seeks to shed light on these processes and their relationships. Our discussion commences with understanding the drivers of donations.

2.1 | Drivers of donations

Humanitarian organizations depend on donations to operate their programs. Several conceptual studies have provided insights into what can drive donations in the context of disaster response. Burkart et al. (2016) conducted a literature survey on the funding-humanitarian supply chain interface; one of their conclusions is that more empirical research is needed to determine the drivers of donors' behaviors.

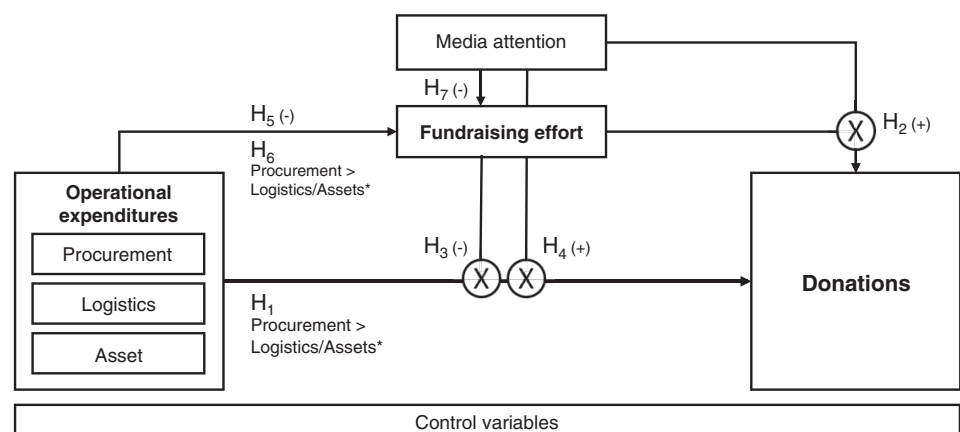


FIGURE 1 Conceptual framework

* indicates that the effect of procurement is expected to be stronger than the effect of logistics or assets, respectively
⊗ indicates an interaction

A considerable number of studies have investigated the drivers of individuals' donations to nonprofits, mostly in the United States. Although we focus on institutional donors, we report shortly the key results of this stream of literature, since some of them contribute to our hypotheses' building. Awareness of needs, fundraising efforts, the stock market, and the number of recipients have been shown to impact donations, in addition to personal characteristics, such as income and altruism (Andreoni, 2008; Andreoni, 2007; Andreoni, Harbaugh, & Vesterlund, 2007; Bekkers & Wiepking, 2011; Brown & Rooney, 2010; Havens & Schervish, 2010; List & Peysakhovich, 2011). Parsons (2007) studied whether individual donors are more willing to donate to humanitarian organizations that, in their fundraising appeals, include financial accounting information regarding their expenditures. We also examine the impact of the financial information contained in the reports but on institutional donors.

The overarching theoretical setting of the framework that we develop is that donors—when making decisions about whether and how much to donate—have only incomplete information available; that is, donors cannot be certain regarding whether the donations will be used effectively, they might be uncertain with regard to the specific severity of a disaster, they might not know whether the IHO is actually capable of achieving the goals that it is advocating, and they might not know whether the IHO's behavior will be in line with the donors' goals. In summary, there is information asymmetry between donors and IHOs because important characteristics of the IHO and/or the disaster are unobservable to potential donors (e.g., Akerlof, 1970; Parsons, 2007). We suggest that donors can reduce this information asymmetry through the information received by the IHOs via fundraising efforts or by relying on media.

In the remainder of this section, we discuss in detail the key drivers of donations that are closest to the focus of this article, and we use them to motivate our hypotheses. The focus in this article is on understanding the drivers of institutional donations organized around three important topics, that is, the impact of operational expenditures (Subsection 2.1.1), the impact of raising donors' awareness (through media attention and fundraising expenditures in Subsection 2.1.2), and their interactions (Subsection 2.1.3).

2.1.1 | Impact of operational expenditures

The most crucial part of budget is that allocated to operational expenditures. These expenses lie at the core of the relief program since they strongly connect with the operations conducted and the impact achieved for the target

population. Previous research has suggested that institutional donors prefer causes that devote a large share of their budgets to operational expenditures, and the share of operational expenditures of the total budget has been called "operational performance" (Eftekhar et al., 2017; Nunnenkamp & Öhler, 2012). One potential reason is that donors have a preference for operational expenditures because they are concerned with value for the money; that is, they disapprove of funding indirect costs since they increase the price of donating (IFRC, 2007; Khanna, Posnett, & Sandler, 1995; Pedraza-Martinez & van Wassenhove, 2016)³. In a similar vein, donors prefer to donate to projects that exhibit low fundraising (Okten & Weisbrod, 2000) and administration costs (Balsam & Harris, 2014; Greenlee & Brown, 1999; Yan & Sloan, 2016).

This notion is reinforced by a second explanation, that is, that operational performance acts as an informational cue that reduces donors' uncertainty. In this sense, the better that the operational performance is, the easier that it is for donors to understand the value that the program as a whole brings to the beneficiaries (IFRC, 2007) and as a result, the lower that the uncertainty is that remains regarding how the IHO will use their funds. Even if donors lack detailed information about the disaster or the organization, they have certainty about the efficiency of the relief program that the organization plans to implement. This reasoning is in line with (Parsons, 2007), who argued that nonprofit organizations attempt to mitigate information asymmetry through detailed financial reports.

Given the discussions above and the consensus in the literature, we expect donors to react, *ceteris paribus*, positively to operational expenditures. However, we contribute to the literature by casting more light on the specific operational components that are most effective in raising donations. We argue that the allocation of the total operational budget to different activities is relevant to donors' decision making (Hyndman & McDonnell, 2009) and that donors have preferences for how the budget should be allocated between different operations and their corresponding operational expenditures.

Previous research has provided conceptual arguments that donors prefer to fund beneficiary-oriented activities, such as procurement, over indirect or other operational costs, such as logistics or assets (van Wassenhove, 2006). In contrast, costs that are not beneficiary oriented, such as logistics or assets, at least until recently were regarded by donors as a back-office function, that is, almost as indirect costs (van Wassenhove, 2006). Hence, having a large share of these nonbeneficiary oriented costs is likely to have less of a positive impact on donations. This reasoning is supported by a report from the IFRC (2007),

which observed that the value of certain costs, such as expenditures on assets that are not directly related to the beneficiaries might be less obvious for donors. An IFRC employee from the Disaster and Crisis Management department during our discussions stated that “procurement is the biggest draw for donors as they can see what goes to who”, highlighting again how, among the different operational expenditures, procurement is perceived to be the expenditure favored by donors. Despite this anecdotal evidence, we are not aware of any empirical research addressing these aspects. In the following, we define the procurement ratio as the procurement/total budget appeal (the other ratios are defined accordingly).

Hence, while we expect all of the operational expenditures to positively affect donations, we expect the effect to be the strongest for procurement, and we propose the following hypothesis:

H_{1A/B} *The impact of the procurement ratio on donations is greater than the impact on donations of (a) the logistics ratio and (b) the assets ratio.*

2.1.2 | Impact of raising awareness

Bekkers and Wiepking (2011) and Karlan, List, and Shafir (2011) showed that need awareness is an important driver of charitable giving, in line with the analytical findings from Aflaki and Pedraza-Martinez (2016). Awareness of a disaster and the associated relief activities can be driven by two main sources. The first is the IHO's fundraising expenditures, which are under the direct control of the organization. The second is the public attention that a disaster receives. Both of these sources of attention are likely to impact donors' motivation, opportunity, and ability to process the relevant information and hence their funding behaviors (MacInnis, Moorman, & Jaworski, 1991).

Fundraising activities, which include advertising and other activities aiming to raise donors' awareness, are the key tools that organizations use to stimulate donation behavior (Okten & Weisbrod, 2000). As such, fundraising serves three direct goals. First, it creates awareness, diminishes information asymmetry (Parsons, 2007), and reduces information costs for donors. Second, it can actively influence donors' preferences since it entails persuasion. Okten and Weisbrod (2000), in a study unrelated to disaster responses and using a large panel data set from U.S. nonprofits, found that fundraising impacts donations positively owing to the information that it conveys to the donors, in line with findings from Eftekhar et al. (2017) and Parsons (2007). Third, donors are likely to be exposed to a multitude of information from

different IHOs and for multiple disaster responses, and previous research has shown that decision makers exposed to too much information will have reduced ability to diligently process all relevant information (MacInnis et al., 1991; Petty & Cacioppo, 1984). Hence, fundraising could be a tool to enhance a decision maker's opportunity and ability to process information by providing focused information about a disaster and to increase motivation by rendering the target disaster response more salient for the donor (MacInnis et al., 1991).

The second driver of attention that contributes to donation behavior is media attention. Strong coverage of a disaster in the mass media will make the disaster and the need for response more salient for potential donors (Bennett & Kottasz, 2000; Olsen, Carstensen, & Høyen, 2003; Waters & Tindall, 2011). Fink and Redaelli (2011) suggested that media attention should drive donations, but they did not measure it directly, leaving it among the unobserved variables. Eftekhar et al. (2017) examined the impact of media attention on private and institutional donations using a panel data set comprised of 23 IHOs over a time period of approximately 11 years on average. They found that media attention is a critical factor in both cases, but while it has an immediate effect on private donations, it has a lagged effect (of one year) in the case of institutional donors. They measured media attention at the organizational level (as opposed to the disaster level) on a yearly basis; this process did not allow them to investigate whether the effect of media is moderated by other disaster- or appeal-specific measures like, for example, operational costs or fundraising efforts. There are three theoretical mechanisms that explain why these effects might occur. First, strong media coverage can render the donors' contributions more visible. Second, the media coverage—in the absence of other information—might serve as a form of external validation to the donor, for example, supporting the donor in the assessment of the magnitude or severity of a disaster. Third, similar to what is described above for the case of fundraising, media might increase donors' motivation, opportunity, and ability to process information about a disaster.

The natural question that now arises is how these two sources of attention interact with each other. Wakolbinger and Toyasaki (2011) reported that more “popular” disasters, that is, those disasters that receive substantial media attention, occasionally receive even too much financial aid. This finding suggests that these cases might require less fundraising efforts than disasters that attract less media attention. Hence, for disasters that receive only little media attention, more fundraising efforts might be necessary to raise the same amount of donations (Balaisyte, Besiou, & van Wassenhove, 2011). These studies have provided some evidence that

fundraising effectiveness depends on media attention, but it is unclear to what extent this effect occurs. We expect that media attention and fundraising reinforce one another, which is particularly evident if we interpret media as a form of external validation to the donor: a donor reached by the fundraising efforts of the IHO that can find validation of the claimed needs in the media will give more weight to the IHO request for the specific disaster response program and vice versa. While the literature has provided conceptual support for this notion, we are not aware of any research that has empirically tested this relationship. Hence, we propose the following hypothesis:

H₂ *The interaction effect between media attention and fundraising effort on donations is positive.*

2.1.3 | Interaction between operational expenditures and awareness

The question then arises of how raising awareness is integrated by donors with other informational cues and potential preferences for certain expenditures. We differentiate between the two types of awareness (fundraising and media attention) that we study and draw on a behavioral theory (i.e., information integration theory) that has been applied in other domains (Granados, Gupta, & Kauffman, 2012) and that is used in situations in which decision makers integrate different types of information. This theory suggests that decision makers place less weight on, say, attribute 1 in their utility function when they also obtain additional information on, for example, attribute 2. We argue that this theory can be generalized to donation behavior. As we outlined above, we expect that donors have preferences for projects that exhibit a large share of operational costs; that is, this information serves as a cue that reduces uncertainty and that hence affects the amount that will be donated. The impact of this cue, however, will be diminished when awareness and the level of information increase through, for example, fundraising efforts. In other words, the positive effect on donations of a large share of operational expenditures will become weaker as the IHO's investment in fundraising increases (or alternatively, the donors' dislike for non-operational expenditures will become weaker). This outcome occurs because fundraising provides donors with information about the program's expected impact and implementation details, in addition to a detailed budget. This increase in donor awareness reduces the information asymmetry between HOs and donors, rendering operational expenditures as an informational cue less relevant. An alternative interpretation of this interaction

would be that a program with a low level of operational expenditures requires more fundraising because the absence of the beneficial cue of a large operational share requires justification and explanation. While Aflaki and Pedraza-Martinez (2016) examined the interaction between awareness and operational performance with an analytical approach, we are, to the best of our knowledge, the first researchers to investigate this interaction effect empirically. This fact is one of the contributions of this research.

In the following, we define the operational ratio as the sum of procurement, logistics, and asset budgeted expenditures divided by the total budget appeal, and we assess the following hypothesis:

H₃ *The interaction effect between fundraising and operational ratio on donations is negative.*

As described above, media is a second means of information for donors. One could argue that information integration theory can also be applied in this case and hence that decision makers will give less weight to their preferences for operational expenditures when media attention is high. What we propose, instead, is that there are stronger effects linked to media attention, which go to the opposite direction. First, we propose that donors might strive for a visible role in disaster response operations since they often attach visibility requirements to their donations (IOM, 2019). In particular, they have policies that regulate the use of their logos (see, for example, ECHO, 2019; Austrian Development Cooperation, 2019). Since more intensive media coverage offers higher visibility, and the operational expenditures are those that offer more visibility (van Wassenhove, 2006; Wakolbinger & Toyasaki, 2011), we expect that the donors' preference for these types of expenditures will be even greater in cases of highly mediatized disasters. Second, if we interpret media as a form of external validation to the donor, we argue that the reasoning goes in the same direction: the more media attention that a disaster receives (e.g., due to its magnitude or severity), the more that the donor will care to ensure that its funds are well spent, that is, that there is lower uncertainty regarding where its funds go. According to our discussion above, this assurance happens when there is a higher ratio of operational expenditures in the budget. Hence, we contribute to the literature by proposing and empirically investigating the following hypothesis regarding the interaction between operations and their respective expenditures with media attention:

H₄ *The interaction effect between media attention and operational ratio on donations is positive.*

2.2 | Drivers of fundraising expenditures

After exploring the determinants of donations, we focus on IHO decision making by examining the drivers of fundraising efforts. Very little is known about potential factors that impact this decision. A few variables that have been identified in the case of charities' fundraising are competition (Aldashev & Verdier, 2010; Rose-Ackerman, 1982) and governmental grants (Andreoni & Payne, 2003). Using the example of the IFRC, we therefore add to the humanitarian literature by investigating the roles of operational expenses and the size of media attention in the decision regarding fundraising expenditures.

2.2.1 | Impact of operational expenditures

As we discussed above in Section 2.1.1, donors prefer to fund operational expenditures. Although the IFRC at the time of our discussions had neither official fundraising policies nor an agreement about tailored fundraising strategies, we still expect experienced fundraisers to consider donors' preferences when planning for fundraising. One potential explanation is that an experienced fundraiser anticipates that, for a high level of operational ratio, she/he needs less fundraising to achieve the same goal. Hence, we propose and test the following hypothesis:

H₅ *The higher that the operational ratio is, the lower that the fundraising expenditures will be.*

We then follow the logic underlying H₁, which suggests that donors prefer beneficiary-oriented activities such as procurement, while costs that are not beneficiary oriented, such as logistics or assets, tend to be regarded as a back-office function (IFRC, 2007; van Wassenhove, 2006) that donors would prefer not to fund. Previous research has not empirically assessed this relationship, and we propose and test the following hypothesis:

H_{6A/B} *The impact of the procurement ratio on fundraising is larger (in absolute size) than the impact on fundraising of (a) the logistics ratio and (b) the assets ratio.*

Since we expect the impacts of all operational ratios to be negative (see H₅), we expect the difference between the effect of procurement ratio and that of logistics (assets) to also be negative.

2.2.2 | Impact of awareness

As described when illustrating the rationale underlying H₂, emergencies that receive high media attention typically need less fundraising (Balaisyte et al., 2011; Wakolbinger & Toyasaki, 2011). Hence, we expect the IFRC to consider this point and plan its fundraising expenditures according to the media attention attracted by the disaster. While the literature has provided conceptual support for this notion, we are not aware of any research that empirically tests this relationship. Hence, we propose the following hypothesis:

H₇ *The higher that the media attention is, the lower that the fundraising expenditures will be.*

Figure 1 summarizes our framework.

3 | METHODOLOGY

3.1 | Data

This article uses data from disaster response (or relief) programs implemented by the IFRC. We collected quantitative data on all IFRC relief programs covering disasters that occurred in the seven-year period between January 2010 and February 2017 and the final reports of which were published before July 2018.⁴ These programs operated in 81 countries. Final reports are issued when a program's operations are completed, and they contain information about the program budget, the donations received and the different types of expenditures. In the specified time range, the IFRC started and completed 174 relief programs. Each disaster response program *i* is one observation in our data set, and our analysis covers all 174 disasters. Some disasters that occurred during the observation period are the “mega” floods in Pakistan and the earthquake in Chile, both in 2010. Across these 174 programs, the IFRC asked for a total 1.85 billion Swiss francs of support, with an average of 6.2 million per disaster. In total, it received 830 million Swiss francs in donations, with an average of 4.77 million per disaster.

3.2 | The IFRC fundraising process

The IFRC is one of the world's largest IHOs operating development programs and responding to natural disasters. We selected this IHO due to its global operations and its focus on natural disasters, for which there are more data available. The IFRC consists of the Secretariat

in Geneva, three logistics units, and 189 National Societies that engage in programs globally.

The IFRC collects funds from different sources. The non-earmarked part of its income comes mainly from the statutory contributions from member National Societies (which in 2015 accounted for 8% of total income) and from a fixed percentage of each donation diverted to the non-earmarked funds (IFRC, 2015). Non-earmarked funds are used mostly to finance the headquarters. In this article, we do not consider non-earmarked fund allocations since they amount to only approximately 1% of the total donations, and our goal is to investigate how donors react to a specific relief appeal request.

The IFRC's donors are mainly institutional (Table 1). In our data set, the institutional donations account for 99%

of total donations, in line with the percentages from the annual report in 2015. In the present research, we focus on institutional donations. National Societies as a whole are the largest donors to the IFRC. In a robustness check (R8), we assess whether National Societies respond differently to appeals, compared to other institutional donors.

Donors can decide whether and how much to donate to each appeal and whether to donate cash or in kind. In-kind donations are accepted only from institutional donors and include goods and transportation (approximately 9% in our data set) and personnel (1% in our data set). In the reports, only the monetary value of the contributions is reported. Therefore, our focal dependent variable is the institutional donations received for a given disaster response program, including both cash and in-kind contributions and excluding non-earmarked allocations.

The IFRC primarily becomes active when a disaster occurs in a country not able to respond without outside support. In these cases, the IFRC supports the local Red Cross or Red Crescent Societies. IFRC first determines the funds necessary to respond to the disaster in collaboration with the national society. Then, it launches a budget appeal, which is available online, to communicate details of the disaster, the response plan, and the budget that the IFRC requests from potential donors. The emergency appeal describes in detail the planned activities and the different budgeted costs.

As soon as the appeal is launched, it is available online. IFRC management reports that data transparency is very important in the organization. Hence, institutional donors can always inform themselves about the specific content of each program. IFRC fundraisers then use the appeal to reach out to potential donors and proactively increase their awareness. We also verified through interviews with staff in the IFRC's HQ that fundraising is carried out by program.

TABLE 1 IFRC donors shares according to IFRC (2015)

Donor	Share of contribution (%)	Top donors
National Societies	60	British Red Cross (11%), Netherlands Red Cross (7.7%), Swedish Red Cross (7.6%)
Governments	29	European Commission (9.7%), United States (7.2%), Japan (4.3%), United Kingdom (3.5%)
Corporate funds	5.6	
Multilateral agencies	3	
Foundations	0.8	
NGOs	0.4	
Individuals	0.9	

Note: individual donors are excluded from our analysis.

TABLE 2 Key expenditure shares in our data set

Category		Report name	Examples	Share (%)
Operational expenditures	Procurement	Relief Items, Construction, Supplies	Shelter, food, seeds and plants, water, sanitation and hygiene, construction materials	56
	Logistics	Logistics, Transport & Storage	Storage, distribution and monitoring, transport and vehicle running costs, logistics services	7
	Assets	Land, Vehicles, and Equipment	Vehicles, computer and telecom, office and household equipment	2
Non-operational expenditures	Other direct costs		For example, salary for personnel on the field, training, travel costs, fundraising	29
	Indirect costs		Percentage of total direct costs that contribute to running, for example, the headquarters	6

3.3 | Measures

Table 2 provides a summary of the relevant IFRC cost categories and its definitions.

We measure *fundraising* through the fundraising expenditures, which are comprised of funds spent on advertising and activities aimed to raise donors' awareness of the specific program. These expenditures are captured by the "Information and Public Relations" entry in the report. Although donor organizations (e.g., the Red Cross National Societies) might spend some funds in fundraising themselves, we do not include these in our estimations since the respective data are not available. Fundraising expenditures vary significantly from one program to another and range between 0 and 7.5% of the total budget appeals in our data set; see Figure 2.

An important control variable in our analysis is the *budget appeal*, which is the total amount that the organization asks for minus the fundraising costs. Our measure for the key operations and their corresponding expenditures is the percentage of the budget appeal (minus fundraising) spent on the operational expenditure.

We measure *disaster magnitude* by the number of people affected by the disaster and who require immediate assistance. We collect disaster magnitude mainly from the EM-DAT database⁵. We match the IFRC reports to disasters in the EM-DAT database, based on the country and date of occurrence. There are some cases in which one report refers to more than one emergency in the EM-DAT; in these cases, we total the disaster magnitudes of

the different events. Furthermore, not all reports have a corresponding entry in the EM-DAT data set; a value for disaster magnitude is available for 124 emergencies from our sample of 174 disasters. The remaining 50 observations were collected directly from the IFRC reports (39 emergencies) and the United Nations High Commissioner for Refugees (UNHCR)⁶ website (11 emergencies). Since most of the observations not having a value of disaster magnitude from the EM-DAT data set involve a population movement (41 of 50) and vice versa (39 of 46 emergencies that involve a population movement do not have an entry in the EM-DAT database), we include a dummy variable for population movement.

We further control for the economic situation of the affected country and use the gross domestic product (GDP), obtained from the C.I.A. World Factbook⁷, as a proxy. Finally, we classify disasters into disaster-type categories, and we include dummies for storms, floods, earthquakes, and population movement as controls. All other disasters comprise the reference category.

A key variable in our analysis is *media attention* (Figure 3). Since there is no publicly available data source that measures media attention for disasters, we rely on a manual collection effort from the Nexis database⁸. We followed previous research (e.g., van Heerde, Gijsbrechts, & Pauwels, 2015) and selected six major media outlets with global reach: The New York Times (from the United States, print and online editions and blogs), The Guardian (from the United Kingdom, print and online editions), The Star (from South Africa, print

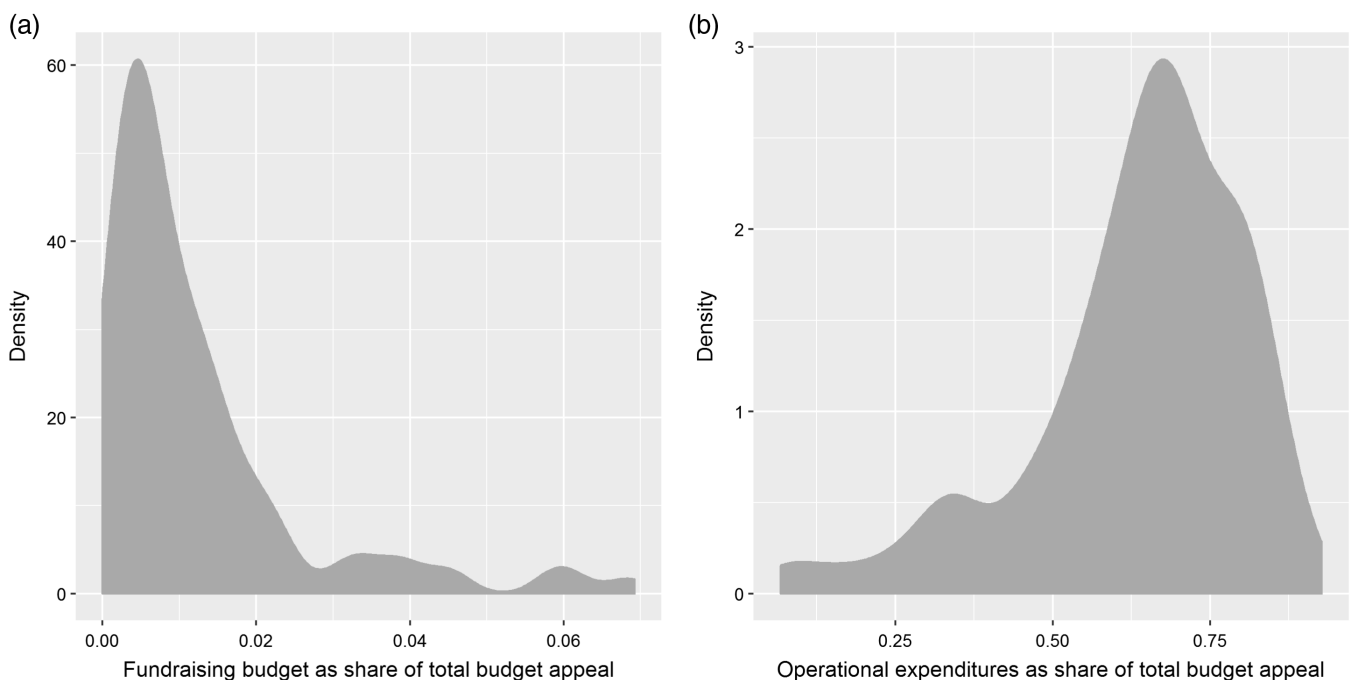


FIGURE 2 Distributions of fundraising budget (a) and operational expenditures (b) as shares of total budget appeal in our data set

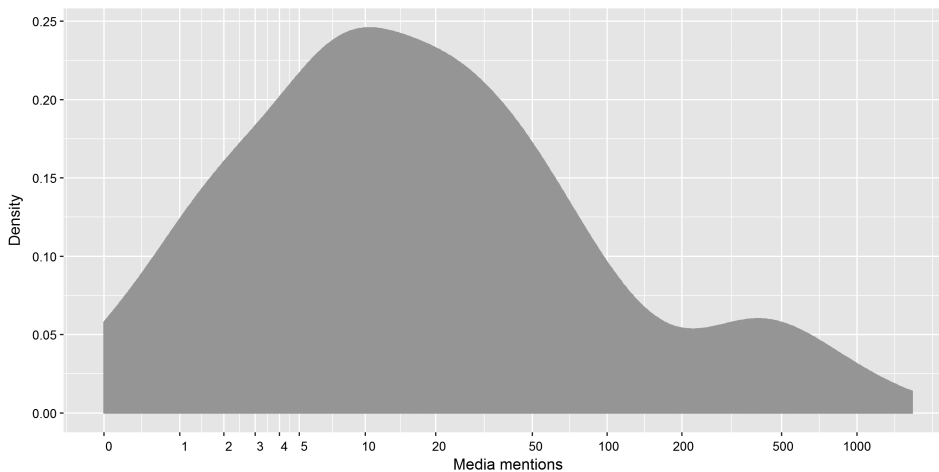


FIGURE 3 Distribution of media mentions in our data set

and online editions), The Japan Times (from Japan, print and online editions), The Strait Times (from Singapore, print and online editions) and The Times of India (from India, online edition). These six newspapers are some of the most widely circulated newspapers available in the English language, and they cover all relevant areas around the globe. Such a rich and diversified collection of media outlets allows us to attain coverage as comprehensive as possible. Within these publications, we counted the number of media mentions (in the whole article, that is, headline plus body of text) for the specific disaster, and we collected media mentions up to 1 year after the disaster. The search results were grouped for “high similarity”; for example, the same article published online and on paper would count only once. The search terms that we used for each disaster were the country in which it occurred in and the type of the disaster; for example, in the case of the Pakistan floods, the search terms were “Pakistan” and “floods.” Four independent judges (two were not coauthors of this article) manually assessed all of the articles that contained the search terms to determine whether they indeed referred to the specific disaster and not to something else. All of the articles that did not refer to the specific disaster were dropped from the list. If an article referred to two distinct disasters, it was counted for both.

This media attention variable serves two central purposes in our study. First, it allows for testing the hypotheses that refer to media attention. Second, it supports us in our identification strategy because this measurement of public attention through media coverage (van Heerde et al., 2015) mitigates the likelihood of unobserved variable bias.

All information that concerns IFRC directly was confirmed through interviews with IFRC management. Specifically, we engaged in discussions with several members of the IFRC managers from the disaster relief

emergency fund, the logistics, the budget and analysis, the strategic partnerships and international relations and the disaster and crisis management departments. We contacted the organization directly when any clarification regarding the data set was needed, and we visited its headquarters in Geneva twice. In these meetings, we discussed (a) the importance of our study for IFRC since there is an increasing push to become more strategic in fundraising allocations; (b) the developed model describing its processes along with the variables used; (c) the results that arose to confirm that they make sense for IFRC; and (d) received feedback that we integrated into the discussion and future research part of this article.

The variables used in the hypotheses and the control variables are categorized and presented in Table 3. In Table 4, we present their descriptive statistics, while their correlation table can be found in Table A1 of Appendix A.

3.4 | Model

Our first set of hypotheses addresses the drivers of donations. We test the relations of the donations received (*Donations*) in response to a disaster with the fundraising expenditure (*Fundraising*), the media coverage (*MediaAttention*), and the extent to which the budget is devoted to operational expenditures (*OperationalRatio*). As outlined in our hypotheses, we then take a closer look at the composition of the operational budget to assess the effects of respective budgeted operational expenditures relative to the budget appeal (for example, $LogisticsRatio = \text{budgeted logistics} / \text{budget appeal}$). The “rest” of the ratio is in both cases the non-operational expenditures divided by the budget appeal (e.g., $OperationalRatio + \text{rest} = 1$ and $ProcurementRatio + LogisticsRatio + AssetRatio + \text{rest} = 1$). Our key control

TABLE 3 Categories of variables included in the hypotheses and control variables

Construct	Variable	Measure description
Donations	<i>Donations</i>	Total donations raised (from institutional donors): Total donations raised minus donations from private donors. The variable includes both cash and in-kind. It does not include unearmarked funds (e.g., DREF allocations). For robustness check R8, they are split between National Societies and rest.
Operational expenditures	<i>OperationalRatio</i>	Proportion of budgeted operational expenditures: (Budgeted procurement + logistics + assets)/budget appeal.
	<i>ProcurementRatio</i>	Proportion of budgeted procurement expenditures: Budgeted procurement/budget appeal. Procurement expenditures: Costs of shelters, clothing and textiles, water and sanitation, food, medical and first aid, construction materials, utensils and tools and other general supplies.
	<i>LogisticsRatio</i>	Proportion of budgeted logistics expenditures: Budgeted logistics/budget appeal. Logistics expenditures: Transportation, vehicle usage, distribution, warehousing and monitoring costs, and logistics services.
	<i>AssetRatio</i>	Proportion of budgeted asset expenditures: Budgeted asset/budget appeal. Asset expenditures: Equipment, vehicles, computers, and telecommunication costs.
Fundraising expenditures	<i>Fundraising</i>	Funds spent in advertising and activities aimed to raise awareness.
	<i>FundraisingSameArea</i>	Average fundraising expenditures of other disasters in the same geographical area.
Media attention	<i>MediaAttention</i>	Media coverage: Number of mentions on the Guardian, the New York times, the star, the Japan times, the strait times and the times of India until up to 1 year after the program's preliminary report publication.
Budget appeal	<i>BudgetAppeal</i>	Total budget IFRC appeals for minus fundraising expenditures.
Country profile		
Strength of economy	<i>GDPpercapita</i>	GDP per capita.
Infrastructure	<i>PavedRoads</i>	Km of paved roads/squared km of country land area.
Development status	<i>HDI</i>	Human development index (HDI).
Geographical area	<i>Area i</i>	Africa ($i = 1$), America (2), Asia Pacific (3), Europe (4) or Middle East and North Africa (5). Area $i = 1$ if the disaster happened in region i , 0 otherwise)
Disaster profile		
Disaster type	<i>Flood, Earthquake, Storm, PopulationMovement</i>	Flood = 1 if the disaster is a flood, 0 otherwise; Storm = 1 if the disaster is a storm, 0 otherwise; Earthquake = 1 if the disaster is an earthquake, 0 otherwise; PopulationMovement = 1 if the disaster is a population movement, 0 otherwise.
Disaster magnitude	<i>DisasterMagnitude</i>	Number of people affected by the disaster and that require immediate assistance (including food, shelter, and medical treatment).
Organization operational and funding profile		
Funding status	<i>FundingPerYear</i>	Total funding received by IFRC during the same year.
	<i>FundingPreviousHalfYear</i>	Total funding received by IFRC during the previous six months.
Operational performance	<i>OperationalPerformance PrevYear</i>	Operational performance of the previous year (operational costs / total funding).
Contextual profile		
Disaster closeness	<i>DaysSinceLastDisaster</i>	Number of days since last disaster occurred.
Disaster incidence	<i>DisastersPerYear</i>	Number of disasters during the same year.
Year	<i>Year i</i>	Year when the disaster took place. 2010 ($i = 1$), 2011 (2), and so forth.
Donor profile:	<i>NationalSociety</i>	NationalSociety = 1 if the donation comes from a National Society, 0 otherwise.

TABLE 4 Descriptive statistics

Model	Variable	Mean	SD	Minimum	Maximum	N
	Donations (in '000)	4,671.4	20,390.5	26.0	238,961.1	174
	OperationalRatio	0.64	0.17	0.07	0.93	174
	ProcurementRatio	0.55	0.19	0.002	0.85	174
	LogisticsRatio	0.07	0.05	0	0.25	174
	AssetRatio	0.02	0.03	0	0.17	174
	Fundraising (in '000)	29.7	115.2	0	1,344.3	174
	MediaAttention	78.8	201.7	0	1,661.0	174
	BudgetAppeal (in '000)	6,237.3	20,943.7	186.6	241,515.1	174
	GDPpercapita	6,137.0	6,303.5	600.0	38,457.0	174
	Flood	0.39	0.49	0	1	174
	Storm	0.13	0.33	0	1	174
	Earthquake	0.04	0.20	0	1	174
	PopulationMovement	0.26	0.44	0	1	174
	DisasterMagnitude (in '000)	1,515.3	2,536.3	1	20,359.5	174
R1	FundraisingSameArea (in '000)	29.7	20.4	8.9	75.8	174
R2.1	DaysSinceLastDisaster	14.56	15.02	0	89	174
R2.2	Year 2010	0.17	0.37	0	1	174
R2.2	Year 2011	0.17	0.37	0	1	174
R2.2	Year 2012	0.17	0.38	0	1	174
R2.2	Year 2013	0.12	0.33	0	1	174
R2.2	Year 2014	0.12	0.33	0	1	174
R2.2	Year 2015	0.14	0.35	0	1	174
R2.2	Year 2016	0.11	0.31	0	1	174
R2.2	Year 2017	0.01	0.01	0	1	174
R2.3	DisastersPerYear	53.3	12.2	29	66	174
R2.4	FundingPerYear (in '000)	127,656.8	131,030.6	244.0	411,998.6	174
R2.5	FundingPreviousHalfYear (in '000)	64,785.0	71,619.9	7,439.2	293,372.4	174
R3	OperationalPerformancePrevYear	0.47	0.05	0.42	.52	174
R4	PavedRoads	0.13	0.26	0.0002	1.97	174
R5	HDI	0.58	0.13	0.35	.94	174
R6	Area 1	0.48	0.50	0	1	174
R6	Area 2	0.15	0.36	0	1	174
R6	Area 3	0.25	0.44	0	1	174
R6	Area 4	0.07	0.25	0	1	174
R6	Area 5	0.05	0.21	0	1	174
R8	Donations (in '000, per donation type)	2,433.6	11,150.4	0.2	169,284.2	334
R8	NationalSociety	0.52	0.50	0	1	334

Note: (Flood = 1, if the disaster is a flood, 0 otherwise; Storm = 1, if the disaster is a storm, 0 otherwise; Earthquake = 1, if the disaster is an earthquake, 0 otherwise; PopulationMovement = 1, if the disaster is a population movement, 0 otherwise; Area i = 1, if the disaster happened in region i , 0 otherwise, please see Table 3 for the areas' coding information; Year i = 1 if the disaster happened in year i). Variables from main models and robustness checks (R1-R8).

variables are *BudgetAppeal* and *DisasterMagnitude* (although part of this variable is likely to be captured already by *BudgetAppeal*, there might be additional

aspects that this variable captures). We include the GDP per capita of the country (*GDPpercapita*) to describe the country profile. We also control for disaster type since

discussions with IFRC management suggested that donors' responses might depend on it. Other variables that were identified in the literature as donation drivers but that are not in the focus of our study (e.g., donor fatigue, political ties) have been tested and included in the robustness analysis (see Section 4.3).

We test hypotheses H₂-H₄ using Model 1:

$$\begin{aligned} \log \text{Donations} = & \beta_0 + \beta_1 \log \text{OperationalRatio} + \beta_2 \log \text{Fundraising} \times \log \text{MediaAttention} + \\ & + \beta_3 \log \text{Fundraising} \times \log \text{OperationalRatio} + \beta_4 \log \text{MediaAttention} \times \log \text{OperationalRatio} + \\ & + \beta_5 \log \text{Fundraising} + \beta_6 \log \text{MediaAttention} + \beta_7 \log \text{BudgetAppeal} + \beta_8 \log \text{DisasterMagnitude} + \\ & + \beta_9 \log \text{GDPpercapita} + \beta_{10} \text{Flood} + \beta_{11} \text{Storm} + \beta_{12} \text{Earthquake} + \beta_{13} \text{PopulationMovement} + \epsilon \end{aligned} \quad (1)$$

We take the log of all metric variables (Eftekhari et al., 2017), which has the advantage that the associated coefficients can be interpreted as elasticities or part of them (Wooldridge, 2009, p. 39). We also add 1 to all metric variables before taking the log to avoid taking the log of zero, and we mean center all variables that are part of an interaction. By mean centering the interacting variables the resulting coefficients are marginal effects at the mean of the moderator; this ensures a straightforward interpretation without the need to calculate marginal effects post estimation (Dawson, 2014).

In order to test H₁, we run a similar model where we disaggregate the operational expenditures by using Model 2:

$$\begin{aligned} \log \text{Donations} = & \beta_0 + \beta_1 \log \text{ProcurementRatio} + \beta_2 \log \text{LogisticsRatio} + \beta_3 \log \text{AssetRatio} + \\ & + \beta_4 \log \text{Fundraising} \times \log \text{MediaAttention} + \beta_5 \log \text{Fundraising} \times \log \text{ProcurementRatio} + \\ & + \beta_6 \log \text{Fundraising} \times \log \text{LogisticsRatio} + \beta_7 \log \text{Fundraising} \times \log \text{AssetRatio} + \\ & + \beta_8 \log \text{MediaAttention} \times \log \text{ProcurementRatio} + \beta_9 \log \text{MediaAttention} \times \log \text{LogisticsRatio} + \\ & + \beta_{10} \log \text{MediaAttention} \times \log \text{AssetRatio} + \beta_{11} \log \text{Fundraising} + \beta_{12} \log \text{MediaAttention} + \\ & + \beta_{13} \log \text{BudgetAppeal} + \beta_{14} \log \text{DisasterMagnitude} + \beta_{15} \log \text{GDPpercapita} + \beta_{16} \text{Flood} + \\ & + \beta_{17} \text{Storm} + \beta_{18} \text{Earthquake} + \beta_{19} \text{PopulationMovement} + \epsilon \end{aligned} \quad (2)$$

To assess H₁, we then calculate and test the differences among the coefficients for procurement (β_1), logistics (β_2), and assets (β_3).

To test our second set of hypotheses on the drivers of fundraising expenditures, we analyze whether or not the fundraising expenditure (*Fundraising*) for a disaster depends on the share of operational expenditures, on the proportions of the different operational expenditures to the budget appeal, and on the media coverage of the disaster. We control for budget appeal because the higher

that the budget appeal is, the more money that the IFRC will spend on fundraising to increase donations. We also control for the disaster magnitude, the country profile (Pedraza-Martinez & van Wassenhove, 2016) and the disaster type. Note that the variable *BudgetAppeal* does not include fundraising expenditures. The same holds for the budget ratios.

We test H₅ and H₇ using Model 3:

$$\begin{aligned} \log \text{Fundraising} = & \beta_0 + \beta_1 \log \text{OperationalRatio} + \beta_2 \log \text{MediaAttention} + \beta_3 \log \text{BudgetAppeal} + \\ & + \beta_4 \log \text{DisasterMagnitude} + \beta_5 \log \text{GDPpercapita} + \beta_6 \text{Flood} + \beta_7 \text{Storm} + \beta_8 \text{Earthquake} + \\ & + \beta_9 \text{PopulationMovement} + \epsilon_i \end{aligned} \quad (3)$$

To test H₆, we run a similar model in which we disaggregate the operational expenditures using Model 4:

$$\begin{aligned} \log \text{Fundraising} = & \beta_0 + \beta_1 \log \text{ProcurementRatio} + \beta_2 \log \text{LogisticsRatio} + \beta_3 \log \text{AssetRatio} + \\ & + \beta_4 \log \text{MediaAttention} + \beta_5 \log \text{BudgetAppeal} + \beta_6 \log \text{DisasterMagnitude} + \beta_7 \log \text{GDPpercapita} + \\ & + \beta_8 \text{Flood} + \beta_9 \text{Storm} + \beta_{10} \text{Earthquake} + \beta_{11} \text{PopulationMovement} + \epsilon_i \end{aligned} \quad (4)$$

and we again calculate the differences among β_1 , β_2 , and β_3 .

3.5 | Estimation and identification

The main goal of our research is to identify the effect of fundraising and the associated interactions that we proposed in our conceptual framework on donations. The key identifying assumption is that our focal regressors are uncorrelated with the error of the model, that is, that there are no important unobserved variables that have a sizeable correlation with both donations and the focal regressors (e.g., fundraising). We follow recent calls to address the issue of identification both theoretically and empirically (Guide & Ketokivi, 2015) and undertake several steps to assure that there are no important unobserved factors. First, we include the budget appeal, controlling for otherwise unobserved characteristics of the disaster and the disaster response. We expect that this variable will pick up a substantial amount of otherwise unobserved variation. Second, we could be concerned about omitted variable bias if public attention to a disaster remains unobserved. To mitigate this concern, we include media attention in the model since the media coverage reflects public attention (van Heerde et al., 2015). This inclusion should substantially alleviate omitted variable problems. This approach is in line with recent developments in empirical research, which emphasize the adverse characteristics of other estimation strategies to mitigate endogeneity concerns (e.g., instrumental variable estimation). According to this line of research, the first choice to address omitted variable concerns should be a “data-rich model” that seeks to eliminate the endogeneity problem by controlling for the factors that cause the trouble (e.g., Archak, Ghose, & Ipeirotis, 2011; Germann, Ebbes, & Grewal, 2015; Rossi, 2014).

Hence, our main identifying assumption is that it is very unlikely that there are important unobserved factors related to donations and fundraising that have sizeable influences on donations (e.g., Rossi, 2014). In a robustness check (R1), we show that the results are very robust if we add instrumental variables and jointly estimate

Models 1 and 3 (the aggregated model) and Models 2 and 4 (the disaggregated model) simultaneously with these additional exclusion restrictions. One additional argument that suggests that any remaining omitted variable bias cannot be of appreciable magnitude is the model fit, indicated by an R^2 of 75 and 80%, respectively, suggesting that most of the variance is explained by observable factors (e.g., Rossi, 2014).

We estimate the coefficients for Models 1–4 using Bayesian estimation. We view this estimation method as attractive because it directly provides inferences about the credibility of parameter values given the observed data, which is less straightforward in traditional statistics (e.g., Kruschke, Aguinis, & Joo, 2012). Further, the Bayesian estimation allows us to incorporate prior knowledge. Based on previous research, we expect that the coefficients (i.e., elasticities) for our focal variables will be close to the interval between 0 and 1, e.g., Okten and Weisbrod (2000) as well as Eftekhari et al. (2017) report coefficients for fundraising between 0 and 0.5. This reasoning is supported by other research, for example, meta-analyses on advertising elasticities (Sethuraman et al. 2011) or personal selling elasticities (Albers et al. 2010) report similar values. Hence, we use a weakly informative prior, that is, we specify normal priors with a zero mean and a SD of 1 (Gelman, Lee, & Guo, 2015), and we proceed accordingly for all regressors. For the intercept, we use a normal prior with a zero mean and a SD of 10. We test several different prior specifications, and all of the results are robust to different specifications (see Appendix C). We generate the posterior distribution using a Hamiltonian Monte Carlo sampler (Stan Development Team, 2016). We run the sampler with four chains for 2,500 draws for a warm-up and 4×2500 draws for inference. All chains are well converged and mixed with a potential scale reduction factor (\hat{R}) of 1. The effective sample size exceeds 5,000 for all coefficients, and the mean effective sample size across all coefficients is greater than 8,500 (Gelman et al., 2013). Hence, we conclude that the resulting Markov Chain Monte Carlo (MCMC) sample is representative of the underlying posterior distribution⁹.

Before we discuss the individual model coefficients, we assess how well the model fits the data. In Figure 4,

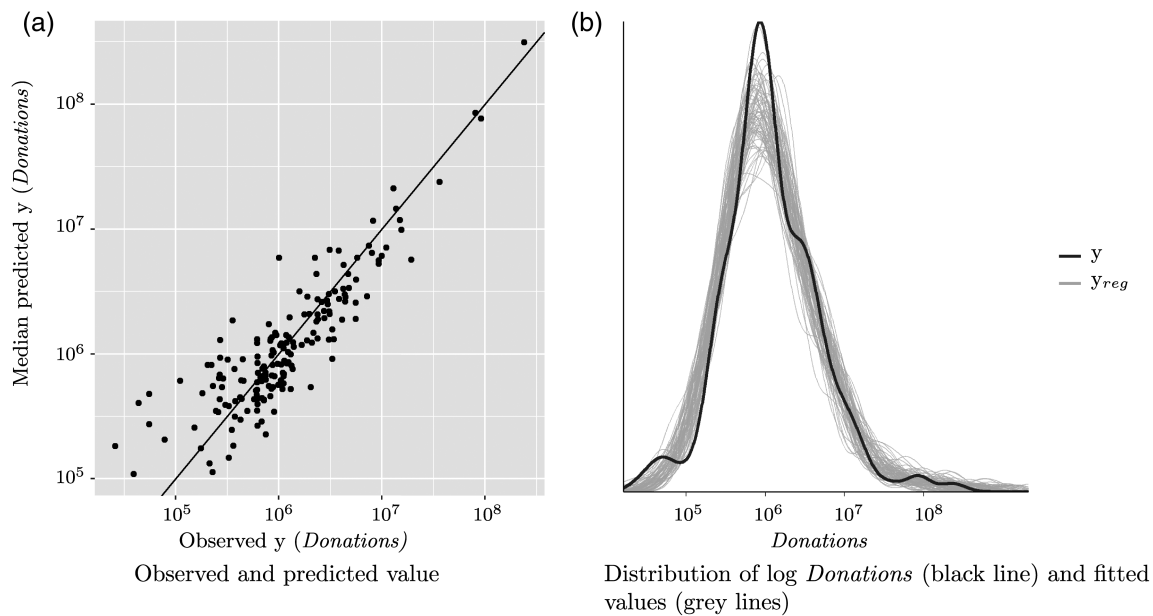


FIGURE 4 Assessment of model fit

Panel A shows a high model fit as predicted, and the observed values are close to the diagonal. Panel B (bold black line) exhibits the distribution of our dependent variable (log *Donations*). The thin gray lines are 75 randomly selected MCMC draws, and the graph indicates that our model captures the distribution of our dependent variable very well. Both graphs are for Model 1, which has a slightly lower R^2 ; accordingly, these graphs provide a conservative picture of model fit.

Finally, all models were diagnosed for heteroskedasticity, nonlinearity, and outliers. No problems were found.

4 | RESULTS

4.1 | Donations

In this subsection, we discuss the drivers of donations for institutional donors. The results of the estimation of Models 1 and 2 are presented in Table 5, while Table 6 shows the results of comparing the coefficients between the different operational expenditures ratios contained in Model 2 (for testing $H_{1A/B}$).

4.1.1 | Impact of operational expenditures

Before we discuss the hypothesis tests, we assess the role of the share of operational expenditures, referred to as operational performance in other studies. In Model 1, the median of the posterior parameter draws is clearly positive.

However, there is substantial uncertainty around the estimate. Although most of the posterior distribution is clearly positive, we cannot unambiguously conclude that the effect is positive. In Model 2, we assess the respective operational categories separately. Interestingly, we see that both logistics and assets are positive and significant, while the posterior interval for procurement is mostly positive but very wide. These results do not appear to be in line with the literature since we expected the positive effect of operational expenditures on donations to be strongest for procurement.

$H_{1A/B}$ formally tests this notion, and Table 6 presents the results of this test. Comparing the coefficients for procurement and logistics, we see no difference of appreciable magnitude since the difference is essentially zero with a wide posterior interval. The comparison between procurement and asset ratios reveals that the difference even tends to be negative, although we again refrain from drawing strong conclusions because of the wide posterior interval of the difference. In essence, these results imply that all three components of operational expenditures affect donations similarly; that is, they tend to be positive, and any differences are statistically insignificant, indicating that the expectation that we formed based on theory, that is, that logistics and assets are a back-office function underappreciated by donors, does not seem to hold. They both affect donations in a similarly positive way as procurement does.

4.1.2 | Impact of awareness

Before we discuss our hypothesis tests regarding awareness, we assess our estimates for the main effect of

TABLE 5 Drivers of donation

Variables	HP	M1					M2				
		Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
		2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio		−0.099	−0.035	0.288	0.609	0.670					
log ProcurementRatio							−0.095	−0.047	0.194	0.433	0.482
log LogisticsRatio							0.010	0.042	0.190	0.337	0.365
log AssetRatio							0.156	0.182	0.307	0.429	0.453
log Fundraising × log MediaAttention	H_2 : +	−0.003	−0.001	0.015	0.031	0.033	0.006	0.008	0.025	0.040	0.043
log Fundraising × log OperationalRatio	H_3 : −	−0.295	−0.279	−0.188	−0.093	−0.076					
log Fundraising × log ProcurementRatio							−0.195	−0.180	−0.106	−0.032	−0.017
log Fundraising × log LogisticsRatio							−0.102	−0.095	−0.061	−0.026	−0.019
log Fundraising × log AssetRatio							−0.105	−0.099	−0.068	−0.036	−0.031
log MediaAttention × log OperationalRatio	H_4 : +	0.074	0.093	0.203	0.312	0.334					
log MediaAttention × log ProcurementRatio							0.017	0.032	0.113	0.195	0.211
log MediaAttention × log LogisticsRatio							<i>−0.006</i>	<i>0.011</i>	<i>0.097</i>	<i>0.188</i>	<i>0.204</i>
log MediaAttention × log AssetRatio							−0.143	−0.128	−0.050	0.024	0.038
log Fundraising		0.064	0.070	0.099	0.129	0.134	0.045	0.050	0.078	0.106	0.111
log MediaAttention		0.037	0.055	0.135	0.215	0.231	0.002	0.018	0.090	0.170	0.184
log BudgetAppeal		0.619	0.638	0.741	0.846	0.866	0.641	0.656	0.759	0.854	0.873
log GDPpercapita		−0.141	−0.118	−0.016	0.089	0.108	−0.076	−0.054	0.040	0.140	0.159
Flood		0.072	0.108	0.305	0.505	0.543	0.090	0.124	0.295	0.469	0.505
Storm		−0.099	−0.048	0.234	0.508	0.564	−0.079	−0.035	0.220	0.468	0.511
Earthquake		−0.451	−0.355	0.094	0.537	0.645	−0.417	−0.329	0.095	0.523	0.596
PopulationMovement		−0.216	−0.175	0.065	0.314	0.355	−0.283	−0.237	−0.020	0.206	0.250
log DisasterMagnitude		−0.020	−0.010	0.036	0.082	0.091	−0.016	−0.008	0.035	0.079	0.086
Intercept		0.290	0.670	2.611	4.447	4.779	<i>−0.228</i>	<i>0.161</i>	<i>1.970</i>	<i>3.763</i>	<i>4.121</i>
Observations		174					174				
R^2		0.75					0.80				

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

fundraising. As anticipated, more fundraising efforts lead to more donations. We find that, on average, an increase in fundraising efforts by 1% leads to an increase in donations by 0.099% in Model 1¹⁰. The 95% posterior interval extends from 0.064 to 0.134. The results do not deviate substantially in Model 2. The effect size is not far from that identified by Okten and Weisbrod (2000), who found

an effect of approximately 0.1. This outcome corroborates our model and results.

H_2 concerns the interaction between fundraising and media attention. This effect is small in size; the median coefficient for Model 1 is 0.015, and for Model 2, it is 0.025. This impact is significant in Model 2 but not in Model 1, in which the 95% posterior distribution includes

TABLE 6 Comparison of regression coefficients for Table 5, Model 2. β_1 is the coefficient for log ProcurementRatio, β_2 for log LogisticsRatio, and β_3 for log AssetsRatio

Coefficients	HP	Percentiles of posterior parameter draws				
		2.5	5	50	95	97.5
$\beta_1 - \beta_2$	H_{1A}^+	-0.287	-0.243	0.000	0.246	0.288
$\beta_1 - \beta_3$	H_{1B}^+	-0.437	-0.380	-0.116	0.156	0.206
$\beta_3 - \beta_2$		-0.135	-0.094	0.117	0.320	0.360
Observations		174				

Note: We do not find any parameter whose 90% posterior interval excludes zero.

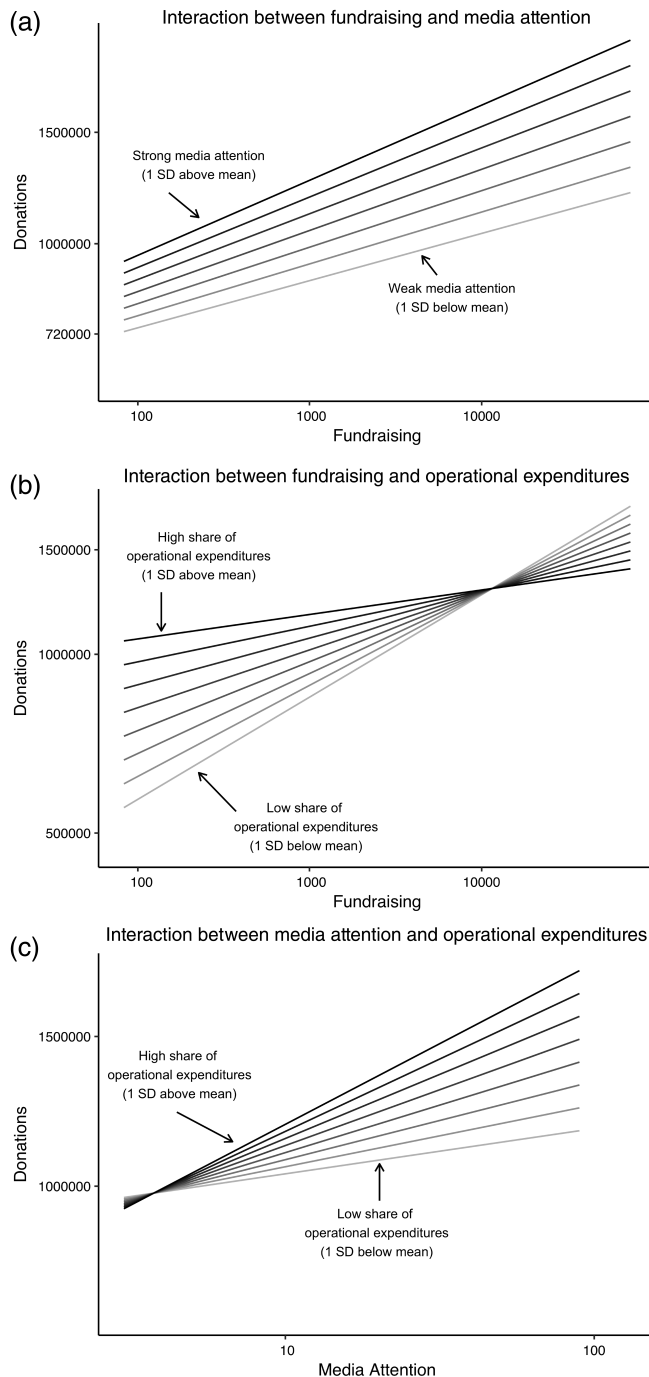


FIGURE 5 Visualization of focal interaction effects

zero. In Figure 5(a), we visualize the interaction. On the horizontal axis, we show *Fundraising* (from 1 SD less than to 1 SD greater than the mean), while the vertical axis shows the predicted *Donations*. Each line then shows the relation between *Fundraising* and *Donations* for different levels of media attention. The light gray line shows the relationship at a low level of media attention (1 SD less than the mean), and the black line represents the highest level of media attention (1 SD greater than the mean). We see that the lines are almost parallel, while the black line (strong media attention) is slightly steeper than the light gray line. Hence, we conclude that the fundraising activities can somewhat benefit from media attention, but the effect is small. These results are interesting since they provide ambivalent support for the notion found in previous research (e.g., Balaisyte et al., 2011; Wakolbinger & Toyasaki, 2011), in which it has been argued that less fundraising is required for “popular” disasters to receive the same amount of donations.

4.1.3 | Interaction between operational expenditures and awareness

H_3 proposes a negative interaction between operational expenditures and fundraising. Our results provide support for this expectation, confirming empirically what Aflaki and Pedraza-Martinez (2016) found analytically. The interaction between the share of operational expenditures and fundraising is negative, and the 95% posterior interval excludes zero, ranging from -0.295 to -0.076 . Examining the different operational categories separately (Model 2), we find that each of them has a significant negative interaction with fundraising, and the sizes of these effects are similar. This outcome indeed suggests that the two cues, fundraising and operational ratio, substitute for one another. While we argued above that more fundraising renders the operational ratio less relevant, one can also make a case for a different interpretation of the interaction, that is, that a large share of operational expenditures renders fundraising less effective, possibly because donors' willingness to donate is already very

high, and further increases are more difficult to achieve. Empirically, these two interpretations are not distinguishable, and both imply that the two cues substitute for each other. We plot the interaction in Figure 5(b). On the horizontal, we display *Fundraising*, while the vertical axis shows the predicted *Donations*. Again, the different lines show the relationship between *Fundraising* and *Donations* for different shares of operational expenditures. We see that the black line, representing the largest share of operational expenditures, is rather flat, indicating a weak relationship between fundraising and donations. For a small share (light gray line), the slope is much steeper, supporting our claim that the interaction between operational expenditures and fundraising is negative.

H₄ concerns the interaction between media attention and operational costs, which we expected to be positive, and the results are in line with this expectation (the coefficient for this interaction is positive, and the 95% posterior interval excludes zero). The effect size is considerable (0.203), suggesting that IHOs can benefit more from media attention if they allocate a larger share of the budget to operational expenditures. Figure 5(c) supports this assessment. Here, on the horizontal axis, we show *MediaAttention*, and the vertical axis represents the predicted *Donations*. We see the steepest slope for a large share of operational expenditures, represented by the black line. The slope for a small share of operational expenditures, represented by a light gray line, is clearly less steep.

When we examine the different operational categories separately (Model 2), we find that the interaction between the procurement ratio and media is positive and significant, with its 95% posterior distribution ranging from 0.017 to 0.211. The interaction between the logistics ratio and media is also positive, but it is only significant at the 90% level (its 90% posterior interval excludes zero, but the 95% one does not). Finally, the assets ratio does not seem to interact with media since its posterior distribution is very wide. This outcome is interesting since, as van Wassenhove (2006) suggested, it might indicate that media attention causes donors to care more for more visible expenses, such as procurement.

In summary, the positive interaction between media and operational ratio suggests that operational expenditures are indeed easier to fund, at least for disasters with high media attention. It seems that this relationship is especially true for procurement and less true for logistics, but it is not true for assets.

In addition to the effects subject to formal hypotheses, the control variables provide relevant insights. An increase in fundraising efforts by 1% leads to an increase in donations of 0.099% in Model 1, which is also the average effect of fundraising on donations. The 95% posterior interval extends from 0.064 to 0.134. The effect magnitude does not

differ substantially from that identified by Okten and Weisbrod (2000). Further, Okten and Weisbrod (2000) compared their uncorrected OLS estimates to the estimates that they obtained from 2SLS. While their 2SLS estimates were very close to the OLS estimates (suggesting that potential endogeneity problems are not substantial), their 2SLS estimates were slightly less than their OLS estimates, and our findings are very close to their 2SLS estimates, further suggesting that endogeneity is very unlikely a problem in our case. Our results differ somewhat from the 0.38 effect identified by Eftekhari et al. (2017). Since they analyzed a set of medium and large IHOs, it might mean that the IFRC's fundraising is less effective than that of the analyzed IHOs.

Further, as expected, media attention leads to more donations; that is, an increase in media attention by 1% increases donations by 0.135% in Model 1, which is also the average effect of media on donations (the results do not change significantly in Model 2). This result is very similar to that from Eftekhari et al. (2017), who found a media coefficient of 0.14. This outcome further corroborates our results, which provide empirical support for the notion that the so-called "CNN-disasters" tend to receive substantial financial support.

The budget appeal is the single most important driver of donations. In other words, if the IFRC asked for a large budget, it typically received a large number of donations; this indicates that the budget appeal also captures other unobserved facets, for example, the trust relationship between IFRC and donors. Hence, this coefficient indicates that large disasters received more donations.

Disaster magnitude has a surprisingly very weak effect on donations, and zero is included in the 95% posterior interval. The reason might be that the budget appeal already accounts for part of the disaster magnitude. Although the correlation between the two variables is only 0.32 (see Table A1), if we run the model without budget appeal, the effect on the disaster magnitude coefficients are significant (see Table B9 in Appendix B). In addition, the effect that we observe might weaken because larger disasters might exhaust donors' capacity such that an increase in donations is not possible because funds are depleted.

4.2 | Fundraising effort

In this subsection, we discuss how the IFRC determines the necessary fundraising expenditure to raise the donations needed for a disaster response program to operate, using Models 3 and 4. The results are presented in Table 7. The results of comparing the coefficients between the different operational expenditures ratios contained in Model 4 can be found in Table 8.

TABLE 7 Drivers of fundraising expenditures

Variables	HP	M3					M4				
		Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
		2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio	H_5 : —	−2.840	−2.645	−1.720	−0.787	−0.586					
log ProcurementRatio							−2.135	−1.983	−1.307	−0.574	−0.425
log LogisticsRatio							−0.363	−0.236	0.433	1.124	1.246
log AssetRatio							−0.522	−0.409	0.161	0.744	0.839
log MediaAttention	H_7 : —	−0.281	−0.209	0.120	0.477	0.546	−0.264	−0.205	0.136	0.470	0.536
log BudgetAppeal		−0.199	−0.117	0.314	0.725	0.795	−0.294	−0.204	0.225	0.637	0.711
log GDPpercapita		−0.242	−0.165	0.268	0.682	0.766	−0.172	−0.089	0.355	0.801	0.885
Flood		−0.805	−0.651	0.130	0.915	1.059	−0.823	−0.669	0.086	0.849	1.003
Storm		−0.269	−0.058	0.960	2.019	2.218	<i>−0.159</i>	<i>0.051</i>	<i>1.031</i>	<i>2.013</i>	<i>2.185</i>
Earthquake		−1.379	−1.132	0.223	1.516	1.775	−1.472	−1.232	0.134	1.503	1.781
PopulationMovement		−1.847	−1.693	−0.815	0.084	0.242	−1.998	−1.851	−0.958	−0.083	0.099
log DisasterMagnitude		−0.196	−0.154	0.053	0.263	0.298	−0.172	−0.129	0.080	0.291	0.333
Intercept		−9.055	−7.739	−0.310	7.039	8.435	−11.617	−10.275	−3.137	4.505	6.061
Observations		174					174				
R^2		0.09					0.10				

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

TABLE 8 Comparison of regression coefficients for Table 7. β_1 is the coefficient for log ProcurementRatio, β_2 for log LogisticsRatio, and β_3 for log AssetsRatio

Variables	HP	Percentiles of posterior parameter draws				
		2.5	5	50	95	97.5
$\beta_1 - \beta_2$	H_{6A} : —	−2.769	−2.602	−1.722	−0.863	−0.681
$\beta_1 - \beta_3$	H_{6B} : —	−2.552	−2.391	−1.460	−0.495	−0.316
$\beta_3 - \beta_2$		−1.407	−1.226	−0.276	0.695	0.887
Observations		174				

Note: In bold are the parameters whose 95% (2.5th to 97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th to 95th percentiles) posterior interval excludes zero are in italics.

4.2.1 | Impact of operational expenditures

In H_5 , we suggest that IFRC's engagement in fundraising will depend on the share of operational expenditures. Our results confirm this expectation since the coefficient is negative, and the 95% posterior interval excludes zero. Thus, in line with Eftekhari et al. (2017), this outcome might imply that the IFRC behaves as if it realizes that donors “like” more programs with higher operational ratios and anticipates a lower fundraising expenditure to raise the same amount of donations (we also tested the

interaction effect between media attention and procurement expenditures on fundraising, but it was not significant).

In Model 4, we assess the respective operational categories separately. Interestingly, we see that the effect of procurement is strong, negative, and significant, while the posterior intervals for logistics and assets are mostly positive and very wide. These results appear to be in line with the theoretical expectations that the effect would be strongest (and negative) for procurement.

$H_{6A/B}$ formally assesses this idea, and the results of this test are presented in Table 8. Comparing the

coefficients for procurement and logistics, we see that the difference is significant and negative. The same outcome occurs when comparing the coefficients for procurement and assets, confirming the theoretical expectation that the IFRC would plan its fundraising budgets mostly based on procurement costs. This outcome is very interesting because it suggests that the IFRC expects donors to prefer procurement expenditures (hence planning less fundraising for higher procurement expenditures) and not as much logistics and assets (hence not planning fundraising according to these). Interestingly, these expectations were exactly those that motivated our hypothesis H_1 and that were not supported in our empirical analysis (i.e., we did not find a difference in effects between procurement and the other operational expenditures on donations).

We should also mention that IFRC managers were surprised when we found that some variables impact fundraising decisions (Table 7) since no fundraising strategy was in place at the time of our discussions to tailor fundraising differently depending on disaster or appeal characteristics. However, they did not exclude that this outcome could occur unconsciously, given the experience and expectations of the employees engaged in fundraising.

4.2.2 | Impact of awareness

H_7 proposes that the IFRC plans lower fundraising expenditures for disasters with higher media attention. Our results do not provide support for this expectation since the posterior distribution is mostly positive. This outcome is surprising considering the idea from the literature that emergencies with high media attention typically require less fundraising (Balaisyte et al., 2011; Wakolbinger & Toyasaki, 2011). This result shows that the IFRC does not approach the fundraising challenge strategically. Although we find support for the notion that higher media attention leads to higher donations, we do not find strong evidence that IFRC considers this point while fundraising since the results (H_7) are associated with considerable uncertainty.

4.3 | Robustness checks

In this section, we outline a set of robustness checks that we employ to assess whether our findings are robust across different model specifications. More details on the implementation and the complete results can be found in Appendix B (Tables B1-B10).

First, as we outlined above, the main identifying assumption of our focal model is that all relevant

variables related to both donations, as well as fundraising, are included in our model, that is, that the error term does not contain important variables correlated with our focal regressors. Although we believe that this assumption is plausible since, from the literature review, no other strong variable arose that our model does not contain, we assess the robustness of our results if we relax this assumption; that is, we estimate a model in which we explicitly treat fundraising as endogenous by estimating a system of simultaneous equations with instrumental variables. This approach is essentially a Bayesian approach to an IV/2SLS estimation. This robustness check (R1) leaves the effect size of the potentially endogenous variable fundraising essentially unchanged, supporting our identification strategy. In our second robustness check, we acknowledge that donors might be subject to *fatigue*¹¹ and donate less when many enormous disasters occur in the same period (Bekkers & Wiepking, 2011). We include five different variables (R2.1-R2.5) to account for donor fatigue in different ways (see Appendix B). We do not find evidence of donor fatigue, which is consistent with the idea that this effect seems to be more present in cases of development aid rather than disaster response (Bennett & Kottasz, 2000; Kevlihan, DeRouen Jr, & Biglaiser, 2014). Third, we assess the effect of the average operational performance¹² of the previous year (the percentage of funds spent on operational expenditures) on donations (R3) because Eftekhar et al. (2017) showed that operational performance impacts institutional donations with a time lag of 1 year. We do not find any impact of this variable in our case, which we explain by noting that (a) we look at disaster response, as opposed to general nonprofit organizations, which means that donors must react more quickly; and (b) the measure of previous-year operational efficiency is a measure used by donors to select the HO to which HO to donate. Since we examine only one organization, it is much more difficult to identify a relation between these two variables over such a short time horizon (we only observe seven values for the variable *OperationalPerformancePreviousYear*). Additionally, we also assessed whether our results depend on the inclusion of other variables, for example, the infrastructure status (R4), since, according to the literature, the state of the roads in particular affects the logistics costs of IHOs (Balcik, Beamon, & Smilowitz, 2008; Kovács & Spens, 2009). We also employed the Human Development Index (HDI)¹³ as an additional measure for the country profile (R5). Next, we acknowledge that donations might be driven by the geopolitical interests of donating countries. To mitigate this concern, we conduct a robustness check that accounts for the region where the disaster occurs (R6). Finally, we report the results of running our model

TABLE 9 Overview of robustness checks for Model 1

Variable/Robustness check	M1	R1	R2.1	R2.2	R2.3	R2.4	R2.5	R3	R4	R5	R6	R7
log OperationalRatio												(+)
log Fundraising × log MediaAttention			(+)	(+)	(+)						(+)	+
log Fundraising × log OperationalRatio	–	–	–	–	–	–	–	–	–	–	–	–
log MediaAttention × log OperationalRatio	+	+	+	+	+	+	+	+	+	+	+	+
log Fundraising	+	+	+	+	+	+	+	+	+	+	+	+
log MediaAttention	+	+	+	+	+	+	+	+	+	+	(+)	+

Note: + (–) denotes a coefficient that is positive (negative) and whose 95% posterior interval excludes zero. Brackets around the + (–) sign indicate that the 90% posterior interval excludes zero, but the 95% includes it.

Abbreviations: M1, original Model 1; Ri, *i*th robustness check model.

TABLE 10 Overview of robustness checks for Model 2

Variable/Robustness check	M2	R1	R2.1	R2.2	R2.3	R2.4	R2.5	R3	R4	R5	R6	R7
log ProcurementRatio												+
log LogisticsRatio	+	(+)	+	+	+	+	+	+	+	+	+	+
log AssetRatio	+	+	+	+	+	+	+	+	+	+	+	+
log Fundraising × log MediaAttention	+	+	+	+	+	+	+	+	+	+	+	+
log Fundraising × log ProcurementRatio	–	–	–	–	–	–	–	–	–	–	–	–
log Fundraising × log LogisticsRatio	–	–	–	–	–	–	–	–	–	–	–	(–)
log Fundraising × log AssetRatio	–	–	–	–	–	–	–	–	–	–	–	(–)
log MediaAttention × log ProcurementRatio	+	+	+	+	+	+	+	+	+	+	+	+
log MediaAttention × log LogisticsRatio	(+)		+	+	(+)	(+)	(+)	(+)	(+)	(+)		
log MediaAttention × log AssetRatio												
log Fundraising	+	(+)	+	+	+	+	+	+	+	+	+	+
log MediaAttention	+	(+)	+	+	(+)	(+)	+	+	(+)	(+)		+

Note: + (–) denotes a coefficient that is positive (negative) and whose 95% posterior interval excludes zero. Brackets around the + (–) sign indicate that the 90% posterior interval excludes zero, but the 95% includes it.

Abbreviations: M2, original Model 2; Ri, *i*th robustness check model.

without budget appeal (R7) to check whether its strong effect influences the rest of the model.

In all the aforementioned robustness checks, the effect sizes of the hypothesis tests remain mostly unaffected (see Table 9 for Model 1 and Table 10 for Model 2). Thus, we conclude that our results are robust with respect to the tested models' modifications.

One additional concern with regard to the analyses that we presented in Sections 3 and 4 could pertain to a substantial share of the donations that we cover being given by national societies that are part of the IFRC, and it is possible that the national societies respond differently to the variables that we consider with respect to other institutional donors. Therefore, our last robustness check (R8) controls for possible heterogeneity between the donors and estimates the differences in donation drivers between National Society and non-National

Society donors. To this end, we augment the data set that we used above and now have for every disaster one observation with donations from national societies and one observation with donations from donors that are entirely independent from IFRC. We then include an interaction between the focal variables and a “national society dummy”. If this interaction is significant or of substantial magnitude, we can conclude that national societies differ in their response. However, none of the interactions with the national society dummy is significant; that is, none of the effects involved in our hypotheses are significantly different between the two sets of donors. Hence, we conclude that we do not have evidence for a substantial degree of heterogeneity between National Societies and the other types of institutional donors with regard to how they respond to fundraising initiatives.

5 | DISCUSSION AND CONCLUSIONS

Demand for humanitarian aid exceeds the donations that IHOs receive (Wakolbinger & Toyasaki, 2011), and this gap is growing (Stumpf et al., 2017). Our article attempts to help IHOs increase the effectiveness of their fundraising by examining how donors' preferences for certain appeal and disaster characteristics can be leveraged in the fundraising process. We propose a conceptual framework that describes how IHOs' operational and fundraising activities impact donations and how they interact with public attention for humanitarian aid in the case of institutional donors and disaster response programs. First, we examine the effect of the operational expenditures ratio and its interactions with media attention and fundraising efforts. While the literature has focused on the direct effects of these variables on donations, to the best of our knowledge, we are the first to focus on the interaction effects. In a second step, we go one level deeper and analyze the effects of specific operational priorities, signaled by their corresponding operational expenditures, on donations. The literature claims that donors prefer beneficiary-oriented expenditures, but to the best of our knowledge, we are the first to empirically validate it. Finally, we examine IHOs' fundraising processes and study whether donors' preferences are considered and whether there are misalignments between IHOs' fundraising efforts and donors' preferences. To the best of our knowledge, we are the first to do so. In our study, we use data from the IFRC and analyze 174 disasters to which the IFRC responded between 2010 and 2017. The proposed conceptual framework is largely supported by our empirical study.

Our analysis provides some novel findings that we now discuss.

(1) *The operational ratio and media attention interact.* The first key implication here is that IHOs engaging in fundraising must consider relevant variables jointly because the effect of one will depend on the level of other; that is, the effect of the operational ratio on donations depends on the level of public attention through the media. One possible explanation is that the visibility that comes from high media attention and operational expenditures (e.g., procurement and distribution of aid) causes donors to donate more. This argument holds under the assumption that donors are interested in visibility. While this argument is conjecture, and our data do not allow us to empirically ascribe this causal explanation to this effect, we view it as a plausible explanation because there is evidence that donors often attach visibility requirements to their donations (IOM, 2019). Further, the effect of operational expenditures unfolds without a (one-year)

delay, which has been shown in cases of general charities. One implication from this outcome is that donors do consider the information provided to them in appeals.

(2) *We find no evidence for differences in the effects of specific operational priorities on donations.* From our results, we conclude that all three components of operational expenditures affect donations in a similar (generally positive) way, and the differences are not statistically significant. Hence, donors seem to consider the operational priorities contained in the appeal, but all three components matter to a similar extent. This finding is significant because, according to the literature presented in Section 2.1.1, donors favor beneficiary-oriented expenditures and do not understand well the importance of logistics. Hence, we were expecting to find a stronger effect of procurement on donations with respect to the other two operational expenditures. However, our results are at odds with this assumption, implying that *the humanitarian operations management literature has not yet fully assessed the impact of specific operational expenditures on donations*. This fact suggests that we must update our view of what donors believe and prefer because, according to our results, assets and logistics expenditures should not be compared to indirect costs anymore but rather should be treated in the same way as procurement.

(3) *Operational expenditures' perceptions depend on the awareness source (media vs. fundraising).* Our results indicate that fundraising informs donors about the importance of the whole budget appeals, reducing the effect of all operational expenditures on donations, while in contrast, media might make it more likely that they develop stronger preferences for certain expenditures, such as procurement. This finding suggests that fundraising substitutes the information that donors obtain from the budget composition, and it weakens the impact of donors' preferences on their donation behavior. Conversely, media attention enhances donors' preferences for operational expenditures, consistent with the notion that donors seek visibility. IHOs should utilize this interaction if it is in their interest or otherwise be aware of it to avoid a misalignment between the donors' perceptions and their needs.

(4) *Fundraising budgets are impacted by procurement expenditures.* The analysis shows that IFRC behaves as if it expects donors to react better to procurement and hence plans lower fundraising expenditures for higher procurement. Interestingly, we do not find evidence for an impact of logistics or asset expenditures, media attention, or other disaster characteristics on fundraising planning. Given that no fundraising strategy is in place at IFRC, these results rather depend on the experience and expectations of the fundraising employees.

(5) *There is a misalignment between donors and IFRC.* Our analysis suggests that the objectives of donors and IHOs, at least in the case of IFRC, are not yet fully aligned. When looking again at Table 5, IFRC could use lower fundraising expenditures for higher logistics or asset expenditures because donors react positively to them. However, as can be seen in Table 7, it does not do so. Additionally, if the goal is to reach a certain level of donations with minimal costs, less fundraising could be planned for highly mediatized disasters. This misalignment between donors and IFRC's objectives could lead to IFRC spending more funds than necessary in fundraising, hence reducing the effective aid provided to the beneficiaries.

The IFRC is a large IHO that is active worldwide, and it attracts substantial donations. At the same time, caution should be used when attempting to generalize our findings to other IHOs. First, the IFRC is an IHO with very strong ties to its institutional donors. In fact, the donations going to IFRC come approximately 60% from their National Societies. Although they are treated as donors by the federation, convincing their own National Societies of the validity of a project might be easier than doing the same with external donors. This concern is, however, made less pressing by our not finding evidence of donor heterogeneity when we augment our data set in our robustness check (R8). Second, the IFRC is one of the largest IHOs worldwide, allowing it to run large programs independently if necessary and to establish programs to be mixtures of different activities. Third, the IFRC preparedness strategy makes use of prepositioning, that is, it stocks essential relief items in three regional logistics units, from which they are shipped to the response locations in the aftermath of a disaster. While this ensures that victims' needs can be satisfied quickly and efficiently, this may potentially impact IFRC's final response budgets, for example, its procurement budget may be lower than that of other organizations for a given set of goals. Additionally, the IFRC has a very high transparency objective that ensures that its budgets are available online when the appeal is launched (with very clear specifications of different budgeted costs). Our study is clearly not generalizable to organizations that do not share the details of their budgeted activities with their donors (in the fundraising phase). Therefore, our results strongly depend on the funding structure of the IHO, and they could only be generalized to other humanitarian organizations similar to the IFRC regarding the types of donors that they attract (almost entirely institutional donors with very strong ties), their operations in cases of disaster response programs (a mixture of food delivery, health and sanitation, shelter building, etc.), their preparedness strategy (prepositioning) and their

transparency with regard to data. Examples of organizations to which our results extend could include the International Committee of the Red Cross (ICRC) and United Nations (UN) organizations such as the World Food Programme (WFP), which also mostly acquire funds from countries that are members of the Geneva Convention and the UN, respectively. Particular caution should be exercised in extending our results to organizations that mostly rely on private donations since preferences for certain types of operations might be different given that private donors generally have less experience in humanitarian operations, less information about the projects and shorter term perspectives.

Our findings have some very important practical implications. For example, the IFRC and similar IHOs could profit from better knowledge regarding how fundraising effectiveness depends both on media attention and on the characteristics of the appeal. Better knowledge of these drivers and of donors' preferences would help to improve the planning of fundraising expenditures. A better fundraising strategy would allow IHOs to save some fundraising costs but achieve the same total donations, hence being able to deliver more aid to the beneficiaries.

Our results also provide useful guidance for donors. We show that the IFRC plans for higher fundraising expenditures when it believes that more effort is required to acquire the necessary funds because of donors' preferences. This misalignment between real and expected donations' drivers could be a lesson for donors: if the IFRC had a better knowledge of their preferences, it would be possible to optimize outputs with less fundraising effort and lower management costs.

The results discussed in this article open opportunities for further research. Since our work represents a first step in the analysis of the operational implications of fundraising, our findings might be used in further studies of the topic. For example, a decision optimization model that models the utilities of the parties could be built. Additionally, researchers might want to extend our study to IHOs that are predominantly funded by private donors. Although institutional donors account for 74% of humanitarian aid worldwide, understanding the behavior of private donors is of great importance. One way to do so could be through an experimental study. As highlighted by IFRC itself, it would also be interesting to benchmark our results against other similar IHOs and create a framework in which organizations can learn from each other and improve their policies. Insights into how different types of donors donate and react to fundraising efforts and how they split their donations between earmarked and non-earmarked funding or between monetary and in-kind donations would also be

very interesting if relevant data are available. Another interesting analysis would be to include the size of the area affected by a disaster. Furthermore, it could be interesting to integrate political aspects into our model (these aspects become even more relevant for organizations operating in cases of man-made disasters) by better understanding the importance of motivation and opportunity in donors' decision-making. In a similar vein, our data typically contain only one disaster per country, not allowing us to directly consider all of the unobserved effects at the country level (e.g., through country-level fixed effects). Furthermore, it would be interesting to analyze the impact of donors' limited capacity on fundraising policies. Additionally, future research should assess whether the IFRC and the donors' decision drivers are the same for development and preparedness programs. This information would help IHOS' managers to target their fundraising efforts appropriately, depending on the program that they plan to run. Finally, another extension of our study could be the optimization of the fundraising decision-making process, which has also been identified by IFRC management as a very important direction for future research.

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ENDNOTES

- ¹ Disaster response is typically funded by private and institutional donors (Burkart, Besiou, & Wakolbinger, 2016). We focus on institutional donors. Examples of institutional donors are governments, the European Community Humanitarian Office (ECHO), and the United States Agency for International Development (USAID).
- ² Logistics include all activities needed for the (a) items supplied for the beneficiaries to be delivered to them; (b) assets; and (c) staff to travel and reach the field. Asset expenditures include the supply of all of the equipment used by IFRC staff. Procurement expenditures include the supply of all of the items used by the beneficiaries.
- ³ Eftekhari et al. (2017) found that the impact of operational performance on donations is delayed by 1 year in the case of charities, which is very reasonable in this context because it is likely the most up-to-date information that donors can access on operational performance. In the present context, however, donors can

assess the operational performance directly in the appeal, which is made known to them in the fundraising process. Hence, we assess whether the operational performance suggested in the appeal affects donors' decision-making. In a robustness check, we assess the role of the previous year's operational performance.

- ⁴ The source is the IFRC website: <https://www.ifrc.org/en/publications-and-reports/appeals>
- ⁵ EM-DAT is an online database maintained by the Centre for Research on the Epidemiology of Disasters (CRED). It contains core data on the occurrence and effects of disasters from 1900 to the present; see <http://www.emdat.be>.
- ⁶ UNHCR, the UN Refugee Agency, is a global organization with a mandate to save lives, protect rights and build a better future for refugees, forcibly displaced communities and stateless people. UNHCR maintains a database that contains data about UNHCR's populations of concern: http://popstats.unhcr.org/en/time_series
- ⁷ <https://www.cia.gov/library/publications/the-world-factbook/>
- ⁸ Nexis is an online database provided by LexisNexis that collects news, company and market insights, biographies and legal and public records. It can be accessed at <https://www.nexis.com/>.
- ⁹ We also note that for the point estimates that we will discuss, the Bayesian estimation gives very similar results compared to a traditional regression. Hence, one can also view the choice of Bayesian estimation as a question of personal preference.
- ¹⁰ We should note that, for the variables involved in interactions, the coefficients are only part of the total effect. For example, the effect of Fundraising on Donations can be calculated as: $\beta_5^* = \beta_2 \log MediaAttention + \beta_3 \log OperationalRatio + \beta_5 \log Fundraising$. Since *MediaAttention* and *OperationalRatio* are both mean centered, the coefficient β_5 is equivalent to the total effect if *MediaAttention* and *OperationalRatio* are their means.
- ¹¹ We thank an anonymous reviewer for this suggestion.
- ¹² We thank an anonymous reviewer for this suggestion.
- ¹³ The HDI is maintained by the United Nations Development Program, and it measures the average achievement of a country based on three key dimensions of human development: long and healthy life; education received; and standard of living. See: <http://hdr.undp.org/en/content/human-development-index-hdi>

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In Table A1, we present the correlation table of our variables.

log Donations	log OperationalRatio	log Procurement Ratio	log Logistics Ratio	log Asset Ratio	log Fundr. × log MediaA.	log Fundr. × log Oper. Ratio	log Fundr. × log Proc. Ratio	log Fundr. × log Log. Ratio	log Fundr. × log Asset Ratio	log Fundraising	log Media Attention	log Budget Appeal	log Disaster Magnitude	log GDP percapita	Flood	Storm	Earthquake	PopulationMovement	log FundraisingSameArea	log DaysSinceLastDisaster	Year 2010	Year 2011	Year 2012	Year 2013	Year 2014	Year 2015	Year 2016	Year 2017	log DisastersPerYear	log FundingPerYear	log FundingPreviousHalfYear	log Oper.Perf.PrevYear	log Oper.Perf.PrevYear × log Fundr.	log PavedRoads	logHDI	Area 1	Area 2	Area 3	Area 4	Area 5
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TABLE A1 (Continued)

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APPENDIX B: ROBUSTNESS CHECKS

Our first robustness check (R1) relaxes the assumption that the error term does not contain important variables correlated with our focal regressors. To this end, we require a variable (“instrument”) related to our focal regressor (i.e., fundraising expenditures) but unrelated to potentially unobserved disaster characteristics. We use as an instrument the average per disaster fundraising expenditures in the same geographical area in which the focal disaster happens (excluding the fundraising for the focal disaster). The rationale is that it is very unlikely that the

fundraising expenditures for disasters in a given region are correlated with the unobservable characteristics of a given disaster in that region. At the same time, it is likely that the fundraising expenditures in a given area are correlated. This identification strategy is similar to instruments used in other domains (e.g., Nevo, 2001). In line with our reasoning, this variable exerts a substantial positive impact on fundraising activities (see Tables B1 and B2). We further assess the incremental R^2 for the instruments, that is, the extent to which the R^2 changes due to the inclusion of the instruments. In general, the R^2 in this equation is modest (0.089), and the inclusion of the

TABLE B1 Robustness check (R1)—Simultaneous equations estimation of Models 1 and 3

		Percentiles of posterior parameter draws				
Model	Variables	2.5	5	50	95	97.5
Donations						
	log OperationalRatio	−0.094	−0.011	0.372	0.767	0.850
	log Fundraising × log MediaAttention	−0.004	−0.001	0.015	0.031	0.034
	log Fundraising × log OperationalRatio	−0.292	−0.274	−0.187	−0.093	−0.076
	log MediaAttention × log OperationalRatio	0.050	0.077	0.197	0.312	0.334
	log Fundraising	0.009	0.036	0.151	0.267	0.298
	log MediaAttention	0.017	0.035	0.125	0.210	0.224
	log BudgetAppeal	0.068	0.595	0.618	0.732	0.838
	log GDPpercapita	−0.161	−0.140	−0.027	0.083	0.104
	Flood	0.039	0.081	0.291	0.506	0.550
	Storm	−0.213	−0.144	0.176	0.476	0.537
	Earthquake	−0.496	−0.399	0.085	0.547	0.638
	PopulationMovement	−0.184	−0.142	0.113	0.383	0.447
	log DisasterMagnitude	−0.027	−0.017	0.035	0.085	0.096
	Intercept	0.421	0.860	2.850	4.997	5.439
Fundraising						
	log OperationalRatio	−3.055	−2.875	−1.898	−0.923	−0.722
	log MediaAttention × log OperationalRatio	−0.484	−0.401	0.066	0.529	0.619
	log MediaAttention	−0.259	−0.199	0.135	0.470	0.534
	log FundraisingSameArea	0.257	0.415	1.170	1.908	2.051
	log BudgetAppeal	−0.073	0.003	0.412	0.819	0.880
	log GDPpercapita	−0.689	−0.591	−0.089	0.389	0.495
	Flood	−0.968	−0.829	−0.054	0.730	0.871
	Storm	−0.543	−0.339	0.641	1.662	1.843
	Earthquake	−1.380	−1.175	0.145	1.456	1.697
	PopulationMovement	−1.705	−1.525	−0.635	0.240	0.423
	log DisasterMagnitude	−0.210	−0.165	0.042	0.253	0.298
	intercept	−12.611	−10.687	−1.833	7.117	9.006
Observations						174

Note: In bold are the parameters whose 95% (2.5th to 97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th to 95th percentiles) posterior interval excludes zero are in italics.

TABLE B2 Robustness check (R1)—Simultaneous equations estimation of Models 2 and 4

Model	Variables	Percentiles of posterior parameter draws				
		2.5	5	50	95	97.5
Donations						
	log ProcurementRatio	−0.095	−0.041	0.246	0.543	0.601
	log LogisticsRatio	−0.020	0.012	0.175	0.335	0.366
	log AssetRatio	0.138	0.165	0.300	0.426	0.452
	log Fundraising × log MediaAttention	0.006	0.009	0.025	0.040	0.043
	log Fundraising × log ProcurementRatio	−0.196	−0.183	−0.108	−0.032	−0.019
	log Fundraising × log LogisticsRatio	−0.101	−0.095	−0.060	−0.026	−0.020
	log Fundraising × log AssetRatio	−0.103	−0.098	−0.067	−0.036	−0.031
	log MediaAttention × log ProcurementRatio	0.018	0.033	0.117	0.205	0.224
	log MediaAttention × log LogisticsRatio	−0.034	−0.011	0.088	0.184	0.206
	log MediaAttention × log AssetRatio	−0.141	−0.126	−0.046	0.036	0.053
	log Fundraising	−0.009	0.013	0.118	0.231	0.256
	log MediaAttention	−0.007	0.008	0.088	0.169	0.186
	log BudgetAppeal	0.621	0.643	0.747	0.847	0.868
	log GDPpercapita	−0.109	−0.088	0.026	0.132	0.151
	Flood	0.063	0.103	0.288	0.467	0.503
	Storm	−0.168	−0.104	0.176	0.447	0.504
	Earthquake	−0.425	−0.344	0.095	0.512	0.595
	PopulationMovement	−0.281	−0.234	0.015	0.271	0.328
	log DisasterMagnitude	−0.025	−0.015	0.033	0.079	0.088
	Intercept	−0.090	0.284	2.283	4.366	4.771
Fundraising						
	log ProcurementRatio	−2.256	−2.133	−1.426	−0.709	−0.562
	log LogisticsRatio	−0.296	−0.163	0.478	1.109	1.218
	log AssetRatio	−0.502	−0.404	0.181	0.739	0.856
	log MediaAttention × log ProcurementRatio	−0.551	−0.469	−0.101	0.265	0.337
	log MediaAttention × log LogisticsRatio	−0.377	−0.298	0.103	0.502	0.588
	log MediaAttention × log AssetRatio	−0.480	−0.415	−0.047	0.319	0.380
	log MediaAttention	−0.313	−0.249	0.097	0.454	0.516
	log FundraisingSameArea	0.218	0.366	1.154	1.906	2.055
	log BudgetAppeal	−0.157	−0.074	0.338	0.747	0.833
	log GDPpercapita	−0.593	−0.484	0.014	0.491	0.590
	Flood	−1.039	−0.907	−0.113	0.689	0.838
	Storm	−0.499	−0.297	0.694	1.684	1.861
	Earthquake	−1.486	−1.239	0.049	1.365	1.595
	PopulationMovement	−1.811	−1.619	−0.714	0.187	0.334
	log DisasterMagnitude	−0.170	−0.128	0.082	0.291	0.334
	Intercept	−16.210	−14.378	−5.631	3.295	5.279
	Observations	174				

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th to 95th percentiles) posterior interval excludes zero are in italics.

TABLE B3 Robustness checks (R2.1-R2.3)—Donor fatigue (Model 1)

Variables	R2.1					R2.2					R2.3				
	Percentiles of posterior parameter draws					Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5	2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio	−0.092	−0.025	0.298	0.609	0.669	−0.161	−0.102	0.236	0.576	0.640	−0.100	−0.036	0.293	0.622	0.678
log Fundraising × log MediaAttention	−0.003	0.000	0.016	0.032	0.035	−0.001	0.002	0.018	0.034	0.037	−0.003	0.000	0.015	0.030	0.034
log Fundraising × log OperationalRatio	−0.297	−0.279	−0.190	−0.098	−0.079	−0.301	−0.283	−0.188	−0.094	−0.078	−0.297	−0.278	−0.186	−0.095	−0.080
log MediaAttention × log OperationalRatio	0.059	0.083	0.190	0.300	0.325	0.074	0.095	0.204	0.316	0.334	0.061	0.086	0.200	0.313	0.334
log Fundraising	0.064	0.070	0.099	0.129	0.135	0.059	0.064	0.095	0.125	0.131	0.064	0.070	0.099	0.129	0.135
log MediaAttention	0.046	0.059	0.139	0.217	0.231	0.051	0.068	0.152	0.236	0.254	0.034	0.050	0.130	0.214	0.229
log BudgetAppeal	0.626	0.645	0.744	0.843	0.861	0.591	0.608	0.711	0.817	0.840	0.619	0.641	0.748	0.850	0.870
log GDPpercapita	−0.139	−0.117	−0.021	0.080	0.097	−0.104	−0.085	0.016	0.120	0.138	−0.133	−0.112	−0.014	0.087	0.103
Flood	0.087	0.127	0.315	0.503	0.539	0.107	0.151	0.348	0.548	0.581	0.075	0.109	0.304	0.497	0.537
Storm	−0.094	−0.042	0.223	0.499	0.550	−0.085	−0.033	0.250	0.530	0.580	−0.089	−0.041	0.233	0.501	0.545
Earthquake	−0.510	−0.435	0.038	0.509	0.589	−0.475	−0.391	0.067	0.515	0.608	−0.426	−0.355	0.123	0.589	0.670
PopulationMovement	−0.208	−0.161	0.067	0.300	0.339	−0.186	−0.140	0.096	0.339	0.379	−0.215	−0.170	0.075	0.302	0.350
log DisasterMagnitude	−0.024	−0.013	0.035	0.081	0.091	−0.029	−0.019	0.030	0.078	0.089	−0.021	−0.012	0.033	0.082	0.091
log DaysSinceLastDisaster	−0.013	−0.012	−0.006	0.000	0.001										
Year 2011						−0.041	0.017	0.316	0.627	0.681					
Year 2012						−0.367	−0.312	−0.008	0.289	0.348					
Year 2013						−0.279	−0.207	0.112	0.440	0.501					
Year 2014						−0.592	−0.525	−0.172	0.160	0.222					
Year 2015						−0.560	−0.494	−0.183	0.132	0.196					
Year 2016						−0.493	−0.425	−0.092	0.249	0.316					
Year 2017						−1.194	−1.001	−0.053	0.922	1.109					
log DisastersPerYear											−0.300	−0.239	0.105	0.431	0.499
Intercept	0.528	0.878	2.677	4.497	4.861	0.461	0.835	2.811	4.736	5.110	−0.793	−0.308	2.107	4.553	5.042
Observations					174					174					174
R ²					0.76					0.76					0.75

Note: In bold are the parameters whose 95% (2.5th - 97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th - 95th percentiles) posterior interval excludes zero are in italics.

TABLE B4 Robustness checks (R2.4-R2.5)—Donor fatigue (Model 1)

Variables	R2.4					R2.5				
	Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio	−0.122	−0.056	0.280	0.601	0.656	−0.131	−0.067	0.256	0.584	0.652
log Fundraising × log MediaAttention	−0.004	−0.001	0.014	0.030	0.033	−0.005	−0.002	0.013	0.029	0.032
log Fundraising × log OperationalRatio	−0.296	−0.279	−0.185	−0.088	−0.068	−0.290	−0.272	−0.179	−0.084	−0.065
log MediaAttention × log OperationalRatio	0.073	0.097	0.208	0.319	0.340	0.078	0.099	0.207	0.320	0.343
log Fundraising	0.064	0.069	0.099	0.128	0.133	0.062	0.069	0.099	0.129	0.135
log MediaAttention	0.046	0.061	0.144	0.227	0.243	0.040	0.058	0.142	0.223	0.237
log BudgetAppeal	0.598	0.617	0.723	0.833	0.854	0.596	0.615	0.721	0.828	0.848
log GDPpercapita	−0.125	−0.107	−0.007	0.091	0.111	−0.132	−0.112	−0.011	0.092	0.110
Flood	0.079	0.116	0.314	0.511	0.544	0.107	0.137	0.327	0.521	0.562
Storm	−0.101	−0.053	0.234	0.509	0.564	−0.116	−0.061	0.226	0.499	0.559
Earthquake	−0.499	−0.409	0.042	0.505	0.587	−0.494	−0.418	0.051	0.518	0.602
PopulationMovement	−0.222	−0.170	0.062	0.294	0.343	−0.209	−0.165	0.078	0.311	0.356
log DisasterMagnitude	−0.022	−0.012	0.036	0.083	0.093	−0.016	−0.008	0.037	0.085	0.095
log FundingPerYear	−0.063	−0.042	0.058	0.158	0.176					
log FundingPreviousHalfYear						−0.042	−0.023	0.081	0.182	0.202
Intercept	−1.087	−0.680	1.736	4.106	4.546	−1.453	−0.968	1.397	3.729	4.202
Observations					174					174
R^2					0.75					0.75

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

instruments substantially increases the R^2 to 0.12, which is an increase by more than 1/3. The F -test ($F = 7.32$, $p < .01$) supports this assessment.

To estimate our model, while considering this exclusion restriction, we estimate Models 1 and 3 (the aggregated models) jointly with correlated errors (after adding to Model 3 the instrumental variable *FundraisingSameArea*). We do the same for Models 2 and 4 (the disaggregated models). This approach is equivalent to an instrumental variable or 2SLS estimator. As before, we rely on a Bayesian estimator and use weakly informative priors and the same number of draws.

The results (Tables B1 and B2) suggest that the magnitude of the effect size of the fundraising variable increases somewhat, but the estimate is associated with substantial uncertainty, caused by the general efficiency loss associated with instrumental variable techniques (Lu, Ding, Peng, & Chuang, 2018). As a consequence, the distribution of the parameter draws is much wider than the single-equation estimation that we reported above.

Importantly, however, the effect sizes of the hypothesis tests are largely unaffected. We therefore conclude that treating fundraising as exogenous, given the controls that we include in our model, is reasonable, and the conclusions regarding the hypothesis tests are unaffected by this decision.

For the remaining robustness checks, we report only the results for Model 1. The results for Model 2 are similar and are omitted (but a summary is provided in Table 10).

Our second robustness check (R2) controls for the possible effect of donor fatigue on donations. We include five variables to account for this effect in different ways: (R2.1) a variable that considers the amount of time elapsed between a disaster and the previous one, in days; (R2.2) the year dummies; (R2.3) a count of how many disasters occur in a given year; (R2.4) how much money was donated in the same given year; and (R2.5) how much money was donated in the six months preceding the disaster. The results (see Tables B3 and B4 for the

TABLE B5 Robustness check (R3)—Operational performance (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	−0.122	−0.053	0.265	0.582	0.645
log Fundraising × log MediaAttention	−0.005	−0.002	0.014	0.029	0.033
log Fundraising × log OperationalRatio	−0.300	−0.283	−0.189	−0.095	−0.075
log MediaAttention × log OperationalRatio	0.067	0.089	0.198	0.306	0.324
log Fundraising	0.064	0.069	0.099	0.129	0.135
log MediaAttention	0.034	0.051	0.132	0.212	0.231
log BudgetAppeal	0.631	0.652	0.755	0.859	0.878
log GDPpercapita	−0.123	−0.105	−0.003	0.095	0.112
Flood	0.079	0.111	0.308	0.500	0.534
Storm	−0.098	−0.047	0.218	0.494	0.547
Earthquake	−0.369	−0.296	0.168	0.621	0.708
PopulationMovement	−0.226	−0.175	0.063	0.296	0.343
log DisasterMagnitude	−0.019	−0.010	0.034	0.081	0.090
log OperationalPerformancePrevYear	−0.659	−0.433	0.850	2.087	2.310
log OperationalPerformancePrevYear × log Fundraising	−0.027	0.024	0.300	0.572	0.613
Intercept	−0.486	−0.133	1.922	3.883	4.287
Observations					174
R^2					0.76

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

TABLE B6 Robustness check (R4)—Infrastructure status (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	−0.114	−0.050	0.284	0.608	0.670
log Fundraising × log MediaAttention	−0.005	−0.001	0.014	0.030	0.033
log Fundraising × log OperationalRatio	−0.283	−0.267	−0.176	−0.082	−0.063
log MediaAttention × log OperationalRatio	0.092	0.110	0.219	0.329	0.349
log Fundraising	0.063	0.069	0.098	0.127	0.132
log MediaAttention	0.023	0.039	0.120	0.203	0.218
log BudgetAppeal	0.635	0.653	0.758	0.859	0.883
log GDPpercapita	−0.213	−0.194	−0.079	0.028	0.050
Flood	0.071	0.108	0.302	0.499	0.536
Storm	−0.148	−0.102	0.169	0.438	0.484
Earthquake	−0.414	−0.334	0.111	0.560	0.651
PopulationMovement	−0.238	−0.192	0.049	0.276	0.318
log DisasterMagnitude	−0.020	−0.011	0.036	0.083	0.091
log PavedRoads	0.127	0.235	0.800	1.353	1.464
Intercept	0.633	0.981	2.808	4.721	5.082
Observations					174
R^2					0.76

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

TABLE B7 Robustness check (R5)—Human development index (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	−0.156	−0.087	0.233	0.568	0.622
log Fundraising × log MediaAttention	−0.004	−0.001	0.015	0.031	0.033
log Fundraising × log OperationalRatio	−0.288	−0.271	−0.177	−0.082	−0.063
log MediaAttention × log OperationalRatio	0.076	0.097	0.209	0.314	0.337
log Fundraising	0.061	0.067	0.096	0.126	0.132
log MediaAttention	0.026	0.043	0.125	0.205	0.221
log BudgetAppeal	0.628	0.648	0.752	0.856	0.878
Flood	0.073	0.107	0.295	0.490	0.529
Storm	−0.124	−0.064	0.201	0.481	0.539
Earthquake	−0.506	−0.424	0.037	0.492	0.572
PopulationMovement	−0.207	−0.169	0.060	0.298	0.353
log DisasterMagnitude	−0.016	−0.006	0.040	0.088	0.096
log HDI	−0.363	−0.243	0.407	1.083	1.201
Intercept	0.008	0.333	2.011	3.701	4.007
Observations					174
R^2					0.76

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

TABLE B8 Robustness check (R6)—Area dummy variables (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	−0.291	−0.215	0.102	0.424	0.482
log Fundraising × log MediaAttention	<i>−0.003</i>	<i>0.000</i>	<i>0.016</i>	<i>0.031</i>	<i>0.033</i>
log Fundraising × log OperationalRatio	−0.263	−0.247	−0.153	−0.062	−0.047
log MediaAttention × log OperationalRatio	0.079	0.098	0.209	0.316	0.341
log Fundraising	0.058	0.064	0.093	0.123	0.129
log MediaAttention	<i>−0.006</i>	<i>0.009</i>	<i>0.091</i>	<i>0.170</i>	<i>0.185</i>
log BudgetAppeal	0.661	0.679	0.781	0.880	0.901
log GDP	−0.378	−0.353	−0.217	−0.078	−0.050
Flood	<i>−0.021</i>	<i>0.018</i>	<i>0.214</i>	<i>0.415</i>	<i>0.456</i>
Storm	−0.195	−0.151	0.124	0.400	0.463
Earthquake	−0.620	−0.528	−0.052	0.402	0.479
PopulationMovement	−0.216	−0.172	0.054	0.293	0.332
log DisasterMagnitude	<i>−0.009</i>	<i>0.002</i>	<i>0.048</i>	<i>0.095</i>	<i>0.105</i>
Area 1	−0.934	−0.834	−0.366	0.113	0.199
Area 2	−0.422	−0.337	0.148	0.629	0.706
Area 3	−0.484	−0.395	0.052	0.504	0.580
Area 4	0.048	0.154	0.683	1.201	1.285
Intercept	1.362	1.732	3.704	5.767	6.147
Observations					174
R^2					0.77

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

TABLE B9 Robustness check (R7)—No budget appeal (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	<i>−0.019</i>	<i>0.069</i>	<i>0.501</i>	<i>0.930</i>	<i>1.009</i>
log Fundraising × log MediaAttention	0.011	0.015	0.036	0.056	0.060
log Fundraising × log OperationalRatio	−0.431	−0.410	−0.287	−0.166	−0.137
log MediaAttention × log OperationalRatio	0.167	0.195	0.339	0.485	0.512
log Fundraising	0.069	0.076	0.117	0.154	0.162
log MediaAttention	0.366	0.385	0.475	0.563	0.580
log GDP	<i>−0.297</i>	<i>−0.273</i>	<i>−0.138</i>	<i>0.001</i>	<i>0.025</i>
Flood	0.126	0.177	0.439	0.687	0.735
Storm	0.013	0.071	0.441	0.803	0.876
Earthquake	<i>−0.452</i>	<i>−0.336</i>	<i>0.273</i>	<i>0.891</i>	<i>1.004</i>
PopulationMovement	<i>−0.474</i>	<i>−0.408</i>	<i>−0.100</i>	<i>0.215</i>	<i>0.268</i>
log DisasterMagnitude	0.009	0.021	0.086	0.150	0.162
Intercept	11.958	12.199	13.707	15.168	15.444
Observations					174
R^2					0.54

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th to 95th percentiles) posterior interval excludes zero are in italics.

results for Model 1) indicate that none of these robustness checks substantially changed the results for the focal variables (e.g., the effect sizes remained very similar), and in none of these specifications did the controls show donor fatigue.

Our third robustness check (R3) controls for the possible effect of the average operational performance of the previous year on donations. We consider the average of this measure for all disasters occurring the year before the observation. For disasters that happened in 2010, which is the first year in our data set, we use the same percentage derived from the annual report for 2009. Since we expect that the operational performance of the previous year might interact with fundraising (the IHO might need more fundraising to counteract a poor operational performance), we include the interaction effect in the robustness check. The results for Model 1 are presented in Table B5 and indicate that this variable is not significant. The interaction effect is positive (but only at the 90% significance level), partially supporting the expectation that more fundraising is needed in cases of poor operational performance. The introduction of these two variables does not impact the hypotheses tests. Similar results hold for Model 2, which we omit.

Our fourth robustness check (R4) controls for the effect of the infrastructure status on donations. We measure the infrastructure status by the ratio of kilometers of paved roads to the squared kilometers of country area;

this calculation provides a measure of the infrastructure network density in the country. This measure is collected from the C.I.A. World Fact Book. The inclusion of the new variable leaves our focal results unchanged (see Table B6).

In the next robustness check (R5), we control for the effect of HDI on donations. Given the very high correlation with GDP (0.89), we employed only one of them at a time. Again, our results remain the same (see Table B7).

In the next robustness check (R6), we control for the effect that the area where the disaster occurs might have on donations. Countries are assigned to areas following the standard UNHCR division: Africa; the Americas; Asia and the Pacific; Europe; and the Middle East and North Africa. The results are very similar to the focal model results; in particular, the coefficients that pertain to our hypotheses and to fundraising are barely affected (see Table B8).

Next, we report the results of running our model without budget appeal (R7), to check whether its strong effect influences the rest of the model. Interestingly, we now find that the effect of the disaster magnitude coefficients is significant, which is explained by IFRC planning the response program according to the disaster magnitude. Few of the coefficients tested in our hypotheses become stronger and more significant (see Table B9).

Finally, we implement a robustness check that compares donations coming from National Societies to those

TABLE B10 Robustness check (R8)—National Society versus Non National Society (Model 1)

Model	Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5
log OperationalRatio	−0.947	−0.829	−0.304	0.226	0.340
log OperationalRatio × NationalSociety	−0.296	−0.178	0.475	1.134	1.266
log Fundraising × log MediaAttention	−0.033	−0.028	0.005	0.038	0.044
log Fundraising × log MediaAttention × NationalSociety	−0.033	−0.023	0.018	0.059	0.067
log MediaAttention × log OperationalRatio	0.024	0.058	0.250	0.444	0.480
log MediaAttention × log OperationalRatio × NationalSociety	−0.390	−0.340	−0.083	0.177	0.232
log Fundraising × log OperationalRatio	−0.325	−0.290	−0.096	0.094	0.131
log Fundraising × log OperationalRatio × NationalSociety	−0.283	−0.243	−0.011	0.228	0.278
log Fundraising	−0.037	−0.027	0.028	0.084	0.094
log Fundraising × NationalSociety	−0.035	−0.019	0.053	0.124	0.137
log MediaAttention	0.026	0.053	0.185	0.318	0.344
log MediaAttention × NationalSociety	−0.298	−0.273	−0.108	0.059	0.093
log BudgetAppeal	0.737	0.779	0.962	1.142	1.180
log BudgetAppeal × NationalSociety	−0.530	−0.479	−0.241	−0.007	0.033
NationalSociety	0.082	0.119	0.342	0.566	0.603
log GDPpercapita	−0.126	−0.105	0.015	0.134	0.159
Flood	−0.106	−0.061	0.167	0.394	0.441
Storm	−0.320	−0.256	0.066	0.394	0.452
Earthquake	−0.653	−0.561	−0.022	0.514	0.631
PopulationMovement	−0.272	−0.212	0.066	0.346	0.401
log DisasterMagnitude	−0.016	−0.007	0.051	0.109	0.119
Intercept	10.543	10.781	12.034	13.363	13.602
Observations					334
R^2					0.54

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.

coming from other donor types (R8). The purpose is to ensure that possible heterogeneity in the donor types does not impact our results. To do so, we use Donations per donor type (National Society vs. non-National Society) as the dependent variable. We also add to the model the dummy variable *NationalSociety*, indicating whether a donation comes from National Societies or not and its interaction with our key variables. National Societies contributed to all 174 disaster relief operations included in our analysis, while non-National Societies only contributed to 160, so we have 334 observations in total for this study. The results are shown in Table B10. The

differences in effects between National Societies and non-National Societies can be observed by examining the coefficients of the variables that interact with the dummy *NationalSociety*: for example, the coefficient of log *OperationalRatio* × *NationalSociety* describes whether the effect of the operational ratio is different between the two sets of donors. Our results show that the only significant difference concerns the effect of budget appeal on donations since its 90% posterior interval includes zero, showing that it is a weaker driver for National Societies. None of the coefficients involved in our hypotheses is significantly different between the two sets of donors.

APPENDIX C: ESTIMATION PROCEDURE

The data analysis, described in Sections 3.3 and 3.4 of the main text, relies on Bayesian estimation. In the following, we briefly outline the key components of this approach.

Bayesian estimation provides an interesting alternative to more traditional statistical methods; accordingly, it has been strongly gaining in reach and usage in recent years across a broad range of disciplines. One of the main reasons for this growth is most likely the increasing availability of software packages that have rendered the previously slow and cumbersome estimation increasingly quick and convenient. While BUGS and Jags were software packages that made Bayesian methods available to a large audience, the most recent addition to this line of packages is Stan, which we use in our estimation (Carpenter et al., 2016).

The key idea of Bayesian estimation is that it combines the data at hand with prior information to arrive at the posterior distribution. The posterior reflects the distribution of the most credible parameter combinations. In other words, Bayesian methods assess the extent to which the data that we have collected change our prior information. This idea is based on Bayes' rule

$$p(\theta|D) = p(D|\theta) \times p(\theta) / p(D) \quad (A1)$$

where $p(D|\theta)$ is the likelihood, $p(\theta)$ is the prior, and $p(D)$ is the evidence. We closely follow the outline and notation of Kruschke et al. (2012), who provided an excellent introduction to the application of Bayesian methods. While the prior and likelihood are relatively straightforward to compute, the denominator $p(D)$ is more difficult because it involves integrating over the entire parameter space, which is usually a very complex problem. The solutions used in applications to circumvent this problem are Markov Chain Monte Carlo (MCMC) methods, which compute an approximation of the posterior by generating a very large “representative random sample of parameter values drawn from the posterior distribution” (Kruschke et al., 2012). Most modern samplers are built such that the user must provide the likelihood, the prior, and the data, and the software then applies the MCMC sampler.

One of the general advantages of Bayesian estimation is that it provides the credibility (or probability) of certain parameters given the data that we observe, allowing for a very direct and intuitive interpretation of the results. In

contrast, a traditional test of a hypothesis informs us about the likelihood of observing these data if the null hypothesis were true (Kruschke et al., 2012), which is a less direct way of interpreting the results.

A second important advantage is the incorporation of prior information into the estimation, which can aid in the analysis of small samples. The prior assigns a distribution of credible parameter values; that is, it assigns higher credibility to plausible parameter values and lower credibility to less plausible parameter values (Kruschke et al., 2012, p. 726). The equation that we estimate in the main text is a log-log-model; hence, all resulting coefficients are elasticities (or part of elasticities). From previous research, we have ample evidence that it is very likely that most elasticities are in the interval between 0 and |1|. Elasticities for fundraising activities of, say, 2 or 3 have never been reported in the literature, and the conceptual similarities with, for example, marketing activities, such as advertising or personal selling, suggest that elasticities of $> |1|$ are not very plausible and thus are very unlikely. Hence, we make the assumption that our parameters will not be far from unit scale (Gelman et al., 2015) and provide this assumption as prior information for our model. More specifically, in our focal model, we use normal priors with a mean of zero and a *SD* of 1 for all response parameters. Since we have no clear a priori expectations with regard to the magnitude of the intercept, we always use a vague prior here (normal(0,10)).

If the data that we combine with the prior to arrive at the posterior distribution are weak, the posterior distribution will be very similar to the prior distribution; that is, in our case, it will be similar to a normal distribution with a center of zero and a *SD* of 1. If the data provided are sufficiently strong, they will overrule the prior provided to the model.

This approach makes it less likely that, given the relatively small sample size, our model arrives at extreme, implausible estimates for our model parameters.

To assess whether our model estimates are sensitive to our choice of a prior distribution, we conducted robustness checks using different prior distributions. Table C1 summarizes the findings of these robustness checks for our focal model (Model 1) across a set of different reasonable prior specifications. The findings clearly suggest that our results are not driven by our choice of a prior distribution.

TABLE C1 Focal model results under different prior distributions, Model 1

Variables	Normal(0,1)					Normal(0,5)					Normal(0,10)				
	Percentiles of posterior parameter draws					Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5	2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio	-0.099	-0.035	0.288	0.609	0.670	-0.101	-0.038	0.296	0.626	0.687	-0.111	-0.040	0.293	0.629	0.698
log Fundraising × log MediaAttention	-0.003	-0.001	0.015	0.031	0.033	-0.003	-0.001	0.015	0.030	0.033	-0.004	-0.001	0.015	0.030	0.033
log Fundraising × log OperationalRatio	-0.295	-0.279	-0.188	-0.093	-0.076	-0.304	-0.285	-0.187	-0.090	-0.071	-0.297	-0.279	-0.186	-0.097	-0.078
log MediaAttention × log OperationalRatio	0.074	0.093	0.203	0.312	0.334	0.066	0.089	0.204	0.313	0.336	0.069	0.092	0.202	0.317	0.339
log Fundraising	0.064	0.070	0.099	0.129	0.134	0.063	0.069	0.099	0.129	0.135	0.066	0.070	0.099	0.129	0.134
log MediaAttention	0.037	0.055	0.135	0.215	0.231	0.033	0.049	0.133	0.214	0.233	0.037	0.052	0.133	0.216	0.233
log BudgetAppeal	0.619	0.638	0.741	0.846	0.866	0.627	0.645	0.745	0.845	0.863	0.617	0.638	0.745	0.847	0.868
log GDPpercapita	-0.141	-0.118	-0.016	0.089	0.108	-0.134	-0.115	-0.016	0.082	0.099	-0.138	-0.117	-0.016	0.085	0.105
Flood	0.072	0.108	0.305	0.505	0.543	0.079	0.120	0.309	0.502	0.541	0.069	0.108	0.309	0.507	0.546
Storm	-0.099	-0.048	0.234	0.508	0.564	-0.095	-0.046	0.238	0.514	0.567	-0.092	-0.045	0.237	0.519	0.573
Earthquake	-0.451	-0.355	0.094	0.537	0.645	-0.475	-0.371	0.101	0.587	0.670	-0.440	-0.360	0.098	0.563	0.660
PopulationMovement	-0.216	-0.175	0.065	0.314	0.355	-0.214	-0.161	0.072	0.310	0.355	-0.218	-0.171	0.070	0.317	0.363
log DisasterMagnitude	-0.020	-0.010	0.036	0.082	0.091	-0.021	-0.012	0.035	0.082	0.089	-0.022	-0.012	0.035	0.082	0.091
Intercept	0.290	0.670	2.611	4.447	4.779	0.333	0.687	2.547	4.456	4.791	0.323	0.660	2.558	4.444	4.857
Observations	174					174					174				
R ²	0.75					0.75					0.75				
Variables	Cauchy(0,1)					Cauchy(0,5)					Student _t (3,0,1)				
	Percentiles of posterior parameter draws					Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
	2.5	5	50	95	97.5	2.5	5	50	95	97.5	2.5	5	50	95	97.5
log OperationalRatio	-0.098	-0.039	0.281	0.599	0.664	-0.097	-0.031	0.295	0.637	0.706	-0.101	-0.041	0.287	0.620	0.679
log Fundraising × log MediaAttention	-0.004	-0.001	0.015	0.030	0.032	-0.004	-0.001	0.015	0.030	0.033	-0.004	-0.001	0.015	0.030	0.033
log Fundraising × log OperationalRatio	-0.292	-0.273	-0.185	-0.092	-0.073	-0.303	-0.284	-0.188	-0.093	-0.077	-0.295	-0.278	-0.185	-0.094	-0.076
log MediaAttention × log OperationalRatio	0.068	0.089	0.203	0.312	0.333	0.071	0.095	0.203	0.307	0.330	0.073	0.094	0.201	0.305	0.326

(Continues)

TABLE C1 (Continued)

	Cauchy(0,1)					Cauchy(0,5)					Student _t (3,0,1)				
	Percentiles of posterior parameter draws					Percentiles of posterior parameter draws					Percentiles of posterior parameter draws				
	0.064	0.070	0.099	0.127	0.133	0.063	0.069	0.099	0.129	0.135	0.063	0.069	0.099	0.129	0.135
log Fundraising															
log MediaAttention	0.038	0.053	0.134	0.214	0.231	0.038	0.052	0.134	0.216	0.230	0.041	0.056	0.135	0.214	0.230
log BudgetAppeal	0.620	0.640	0.741	0.847	0.870	0.622	0.640	0.744	0.847	0.864	0.618	0.640	0.741	0.844	0.862
log GDPpercapita	−0.136	−0.116	−0.016	0.083	0.099	−0.137	−0.118	−0.014	0.084	0.100	−0.140	−0.120	−0.016	0.084	0.104
Flood	0.074	0.112	0.303	0.500	0.538	0.066	0.105	0.306	0.508	0.542	0.082	0.117	0.303	0.501	0.534
Storm	−0.095	−0.042	0.227	0.497	0.548	−0.094	−0.039	0.241	0.513	0.562	−0.097	−0.041	0.232	0.510	0.557
Earthquake	−0.438	−0.362	0.092	0.551	0.644	−0.469	−0.373	0.105	0.585	0.679	−0.455	−0.364	0.102	0.562	0.666
PopulationMovement	−0.205	−0.161	0.067	0.299	0.347	−0.205	−0.161	0.073	0.309	0.342	−0.210	−0.166	0.075	0.309	0.344
log DisasterMagnitude	−0.020	−0.011	0.035	0.083	0.092	−0.023	−0.013	0.035	0.081	0.089	−0.021	−0.012	0.035	0.084	0.094
Intercept	0.349	0.752	2.609	4.484	4.827	0.407	0.717	2.547	4.487	4.887	0.314	0.685	2.624	4.527	4.899
Observations	174					174					174				
R ²	0.75					0.75					0.75				

Note: In bold are the parameters whose 95% (2.5th–97.5th percentiles) posterior interval excludes zero. Those parameters whose 90% (5th–95th percentiles) posterior interval excludes zero are in italics.