STRATEGIES TO ACCESS AND MANAGE DONATIONS FOR HUMANITARIAN OPERATIONS

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To Sebastián,

Siempre juntos

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Chapter 1. Introduction

1.1. Background

Natural disasters and conflicts have risen both in frequency and in impact over the years due to an increase of global population, climate change and technological complexity (Starr & Van Wassenhove, 2014). Unfortunately, humanitarian funding is not growing as fast as humanitarian needs. In 2016, donations for international humanitarian assistance reached US$27.3 billion increasing 6% from the assistance given in 2015. Although this is equivalent to collecting US$3.6 from each person in the world, this funding presented a shortfall of 40% when compared to the appeals (Lattimer et al., 2017). This situation compels humanitarian organizations (HOs) to look for alternative ways to access donations and to manage more efficiently their current resources. The objective of this dissertation is to study the strategies HOs can use to access and manage donations from donors.

Donations are important resources because they determine the scope, speed, effectiveness and efficiency of any humanitarian response (Burkart, Besiou, & Wakolbinger, 2016; Wakolbinger & Toyasaki, 2014). Donations can take different forms such as cash, time or in-kind items, and can come from different sources such as institutional donors (e.g., governmental and nongovernmental entities) or private donors (e.g., individuals and private companies). In this dissertation, I focus on cash and time donations from governmental agencies and individuals. Regardless of their nature or source, accessing and managing donations from donors are a challenge for HOs. Previous research about the relationship between donors and HOs has focused on the active and constraining role of donors when giving donations (Aflaki & Pedraza-Martinez, 2016; Besiou, Pedraza-Martinez, & Van Wassenhove, 2012; Burkart et al., 2016), while considering the role of HOs as a rather passive one. Instead, I argue that HOs also have an active agency in the processes of accessing and managing donations.

The aim of this introduction is two-fold. First, I review the literature on donations for humanitarian operations in combination with other streams of research, such as resource dependence theory, crowdfunding and volunteering. Second, I set the research agenda that motivates this dissertation, considering that HOs have an active role in the processes of accessing and managing scarce financial and time donations. To achieve these objectives, I use two perspectives: organizational and individual. From an organizational perspective, I study the relationship of HOs with institutional donors (governmental agencies). From an individual perspective, I consider the rapport of HOs with private individual donors.

1.2. The Humanitarian Setting and the Role of Donations

HOs work on designing and implementing programs in order to alleviate human suffering caused by disasters (relief programs) and to improve the quality of life of the society through community sustainability (development programs) (Beamon & Balcik, 2008; Besiou et al., 2011). One practical example of HOs' work is the response given to Haiti after Hurricane Matthew struck the country on October 3 2016, affecting over two million people. By October 10, an appeal of US$119 was launched and HOs started to respond to humanitarian needs with different projects in diverse sectors such as emergency shelter (accommodating displaced population), food security (distributing food), health and nutrition (preventing diseases such as cholera and malaria), education (repairing damaged schools) and water, sanitation and hygiene (distributing drinking water and repairing latrines).

To carry out their programs, HOs interact with multiple stakeholders. Interactions with humanitarian supply chain actors such as donors, suppliers, governments and nongovernmental organizations allow HOs to get the financial, material and informational resources to run their operations. Despite the diversity of actors in the humanitarian supply chain (Van Wassenhove & Pedraza-Martinez, 2012), the relationship with donors is the most critical one for the survival of HOs, because HOs depend on donations to fund their operations.

The nature of donations can be categorized as cash, time or in-kind. Cash donations refer to monetary resources that HOs can use to procure the items required for a response. Time donations refer to volunteering activities, in which people donate their time and work to HOs (Burkart et al., 2016; Holguín-Veras, Jaller, Van Wassenhove, Pérez, & Wachtendorf, 2014). In-kind donations refer to material resources such as relief items (e.g. food and medical kits) or anatomical donations (e.g. blood and organs), which allow HOs to avoid the procurement process. These donations may come from different sources, in particular, from institutional or private donors. Institutional donors are usually large funding agencies from governments, while private donors are individuals willing to give their money or time to humanitarian causes (Burkart et al., 2016).

However, accessing and managing donations both from institutional and private donors are a challenge for HOs. Accessing donations is difficult due to the competition among HOs for donor attention and funding (Oloruntoba & Gray, 2006; Van Wassenhove, 2006). Competition for donations peaks during early phases of the response, when disasters receive media attention and financial resources are readily available (Lindenberg, 2001; Stephenson & Schnitzer, 2006). Such competition can lead to negative operational outcomes, such as hampering coordination and reducing overall performance when it comes to aid distribution (Balcik, Beamon, Krejci, Muramatsu, & Ramirez, 2010; Stephenson, 2005). For instance, HOs may hide important information to their counterparts, if they believe that this will hinder them from attracting donor attention (Balcik et al., 2010; Stephenson, 2005).

Managing donations can also be a challenge due to different pressures donors pose on results and on the scope of a response. Donors ask HOs to deliver aid in an accountable and cost-effective fashion (Leiras, de Brito Jr, Queiroz Peres, Rejane Bertazzo, & Tsugunobu Yoshida Yoshizaki, 2014; Thomas & Kopczak, 2005; Van Wassenhove, 2006). This requirement usually means increasing the budget allocated to relief items while reducing the budget for training and other activities that could be considered as overhead costs (Kovács & Spens, 2007). Another pressure is about the scope of the response because donors can make use of earmarking, i.e. conditioning the use of funding provided (Besiou et al., 2012; Pedraza-Martinez, Stapleton, & Van Wassenhove, 2011). Earmarking usually focuses on short-term relief operations and aid distribution, instead of long-term investments in systems and processes (Besiou et al., 2011; Oloruntoba & Gray, 2006).

Given the criticality of the relationship between donors and HOs, this dissertation focuses on the donation process. I take two perspectives: an organizational and an individual perspective, emphasizing the active role that HOs have when accessing and managing resources. I first review different streams of research related to each perspective and identify gaps and opportunities that remain open. Then, I suggest research questions as avenues for future studies to seize those opportunities. Finally, I show how the different chapters of this dissertation contribute to the proposed research agenda.

1.3. An Organizational Perspective on Donations: Accessing Financial Donations from Institutional Donors

In 2016, institutional donors gave US$20.3 billion to humanitarian response projects, which represents a growth of 6% compared to donations of 2015 (Lattimer et al., 2017).

Nevertheless, this increase is the smallest one in the last 4 years. In fact, the percentage growth of institutional donations has been shrinking over the years (26% in 2014, 9% in 2015 and only 6% in 2016), which poses challenges for HOs to get the required financial resources to run their operations. Consequently, HOs need to develop strategies to access scarce funding from institutional donors.

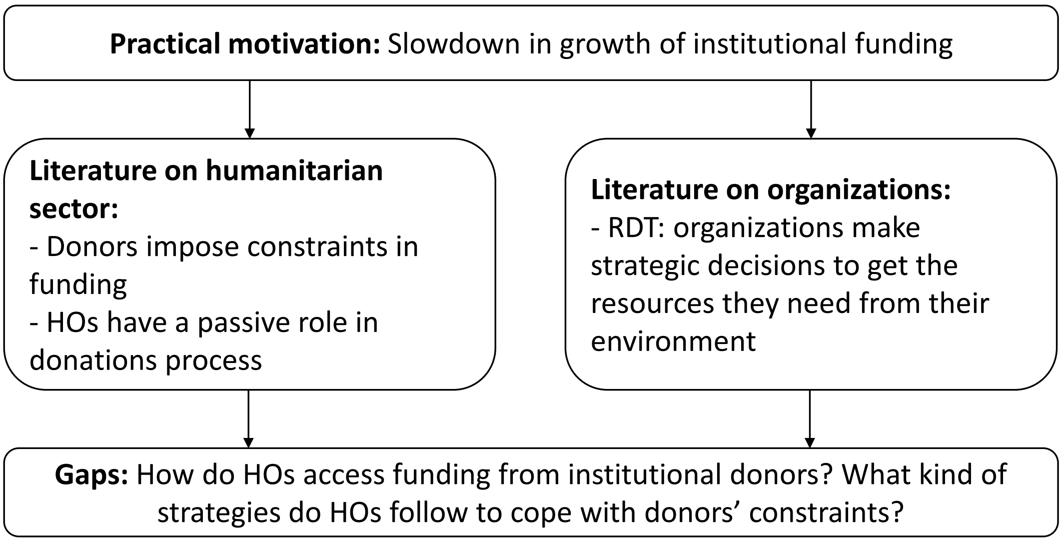
Organizations comprise a complex set of social processes beyond the internal decision-making and organizational structure, involving processes that take place in the environment outside the organization (Scott & Davis, 2007). The environment in which HOs are immersed is highly complex, due to multiple interdependencies and high environmental uncertainty. On the one hand, HOs need to coordinate many interdependencies with various external stakeholders such as donors, suppliers, beneficiaries, government, military, other HOs, and private organizations (Besiou et al., 2011; Starr & Van Wassenhove, 2014; Van Wassenhove & Pedraza-Martinez, 2012). On the other hand, HOs have to deal with high uncertainty because they cannot predict when and where a disaster will occur and how intense it would be. Therefore, HOs cannot accurately determine ad hoc how many people will need help (demand) and where to allocate the available resources (Balcik et al., 2010; Van Wassenhove & Pedraza-Martinez, 2012). In addition to the demand uncertainty, HOs also deal with supply uncertainty. Donor generosity varies over time and for each type of response, which makes it challenging for HOs to plan and effectively satisfy the needs of the affected population (Tomasini & Van Wassenhove, 2009).

One of the theories to study the way organizations obtain external resources from stakeholders in highly complex and uncertain environments is resource dependence theory (RDT). RDT originates from the principle that organizations are not self-sufficient and they cannot internally generate all the resources they need (Pfeffer & Salancik, 1978). Quite opposite, organizations are dependent on the environment and key to their survival is the ability to acquire and maintain resources in exchanges with external stakeholders (Amezcua, Grimes, Bradley, & Wiklund, 2013; Dieleman & Boddewyn, 2012; Wry, Cobb, & Aldrich, 2013). Furthermore, when organizations face important environmental complexity, they need to increase their strategic activities to reduce uncertainty in the acquisition of critical resources (Aldrich, 1979). Strategies can be categorized as unilateral or bilateral (Casciaro & Piskorski, 2005). Unilateral strategies reduce the dependence of one organization on a stakeholder by increasing the sources of supply for the needed resource (Emerson, 1962). Bilateral strategies focus on balancing the power by aiming directly to the constraining stakeholder. Some of these bilateral strategies are mergers and acquisitions, joint ventures, strategic alliances and interlocking directorates (Casciaro & Piskorski, 2005; Davis & Cobb, 2010; Dieleman & Boddewyn, 2012; Drees & Heugens, 2013; Hillman, Withers, & Collins, 2009; Pfeffer & Salancik, 1978; Wry et al., 2013).

As HOs need to access financial resources from institutional donors for their survival (Aflaki & Pedraza-Martinez, 2016; Starr & Van Wassenhove, 2014), RDT predicts that HOs will look for strategic ways to manage uncertainty, so that they can acquire and maintain the flow of funds to run their operations (Casciaro & Piskorski, 2005; Davis & Cobb, 2010; Dieleman & Boddewyn, 2012; Pfeffer & Salancik, 1978). However, most of the literature has framed the donation process to be only under the control of donors. This approach can be problematic, because it leaves HOs in a helpless situation and completely dependent on donors' will. If we change the perspective and consider the possibility that HOs can have an active role during the process of accessing funding, we could be able to identify the kinds of strategies that improve the ability of HOs to obtain financial resources from donors and under what conditions those strategies work best. This approach is especially important nowadays given the slowdown on the growth of institutional donations (Lattimer et al., 2017).

I consider that future research on the relationship between HOs and institutional donors could benefit from organizational theories such as RDT, which gives HOs increased agency in the process of acquiring resources. Related research questions are: *How do HOs access the financial resources from institutional donors to run their operations? What kind of strategies allow HOs to access financial resources and why do they work? What is the effect of different strategies on other managerial decisions of HOs?* Figure 1.1 summarizes my arguments.

Figure 1.1 Summary diagram on accessing financial donations from institutional donors



1.4. An Individual Perspective on Donations: Accessing Financial Donations from Private Donors

In the last decade, donations from individual private donors have become more important for HOs (Kovács & Spens, 2007; Thomas & Kopczak, 2005). Individuals donate money to support humanitarian action and their donations are not negligible. Financial private donations for humanitarian assistance added up to US$6.9 billion in 2016, equivalent to 25% of the total donations (Lattimer et al., 2017). Therefore, HOs can potentiate the opportunity of accessing private donations by understanding the motivations and incentives people have to donate.

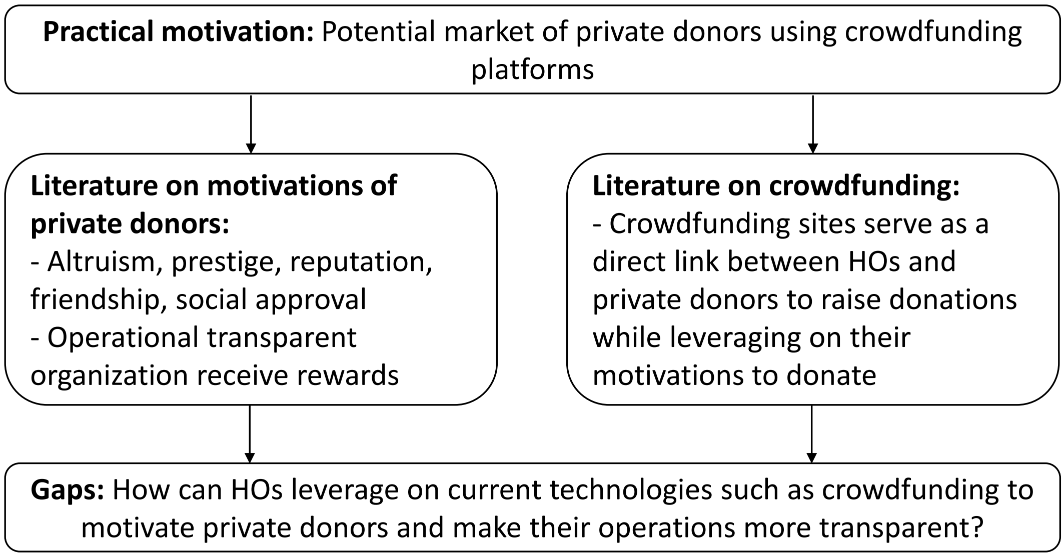
Individual motivations to donate have been a subject of previous research in different streams of literature. From a rational perspective, individuals are self-interested and would not have economic incentives to donate to a charitable cause out of pure altruism. Andreoni (1989, 1990) argues that a model of pure altruism cannot explain observed patterns of giving that a model of "impure" altruism can. An impure altruistic model combines the assumption of altruism with the warm glow; i.e. the internal satisfaction people feel when giving to others. Other researchers consider that to understand the motives to donate, it is necessary to go beyond economic models and move toward other social and psychological incentives such as the desire to gain prestige, reputation, friendship, respect and social approval (Harbaugh, 1998; Holländer, 1990; Olson, 1965). Further experimental research shows evidence that people can actually have a prosocial nature for cooperation, supporting the altruistic hypothesis (Eckel & Grossman, 1996; Fehr & Fischbacher, 2003; Fehr & Gächter, 2002; Henrich et al., 2006). HOs have attempted to align their organizational activities with the individual motivations of private donors. For instance, HOs have usually appealed to the social motivations to donate by giving recognition to their donors, which can go from a small sticker to an official acknowledgement in their websites.

In addition, HOs use different messages and channels in reaching private donors. To increase donations, HOs use communication strategies such as emphasizing their commitment to preparedness and training programs or giving cards to identify the donor as an organization's supporter (Ryzhov, Han, & Bradić, 2016). Moreover, HOs can positively influence the generosity of private donors by designing their communications in a way that prime donors with their identity as previous supporters or members of a community (Kessler & Milkman, 2016). Regarding channels, HOs can have volunteers go on the streets to raise funds by talking directly to people and taking advantage of the empathy these kinds of situations create (Andreoni, Rao, & Trachtman, 2017). They also use direct-mail marketing to foster repeated contributions from previous donors.

A novel channel to reach potential donors of cash is through the use of social media. In particular, I consider the high potential of online crowdfunding platforms to raise money for humanitarian causes. Crowdfunding is a mechanism through which individuals and organizations raise money from a large number of people (i.e., the "crowd"), whose singular contributions are usually small (Belleflamme, Lambert, & Schwienbacher, 2014). There are four types of crowdfunding: equity-, lending-, reward- and donation-based. In equity-based crowdfunding, funders act as investors who support an entrepreneur and expect future returns of their investment. In lending-crowdfunding, funders act as lenders who give their money in exchange for interest. In reward-based crowdfunding, funders act as investors who support an enterprise or project in exchange for a non-financial benefit. In donation-based crowdfunding, funders act as donors who give money to support a cause without getting tangible rewards in return (Brüntje & Gajda, 2016; Kuppuswamy & L.Bayus, 2015). Donation-based crowdfunding not only allows HOs to reach out to private donors more directly, but also to provide more targeted information about the operations performed with a specific given donation. Considering that people tend to reward organizations that are transparent with their operations in a direct manner (Buell, Kim, & Tsay, 2017; Buell & Norton, 2011), I believe that HOs will benefit from actions that will disclose their operations to their individual donors in a more accessible way.

There is currently an opportunity to advance the research at the intersection of the humanitarian operations literature, operational transparency and crowdfunding. First, building on previous findings, future research can investigate how HOs can make the best use of new online channels such as crowdfunding to raise cash donations from individual donors. Second, future studies can look into the effect of operational transparency on private donations in general, and on online crowdfunding donations in particular. Possible research questions are *how can HOs leverage on current technologies such as crowdfunding to make their operations more transparent? How does this transparency affect the outcome of crowdfunding campaigns? How can HOs communicate more efficiently their operational transparency?* Figure 1.2 summarizes my arguments.

Figure 1.2 Summary diagram on accessing financial donations from private donors



1.5. An Individual Perspective on Donations: Managing Time Donations from Private Donors

In addition to financial support, individual donors can give their time to HOs, which is also known as volunteering. In fact, around 45% of US residents reported to have volunteered for charities at least once a month during 2015 (Independent-Sector, 2016). However, volunteer management can be challenging for HOs, given the three main particularities of this kind of donations. First, given the lack of formal contracts between HOs and volunteers, there is always uncertainty regarding volunteer arrivals and the length of their stay in the organization (Sampson, 2006; Wisner, Stringfellow, Youngdahl, & Parker, 2005). Second, there is high variability of volunteer skills and experience, which creates a challenge for HOs to plan their activities without having a stable skill set (Lassiter, Khademi, & Taaffe, 2015). Third, there is the issue of convergence, on which a large part of the earlier literature on volunteer management focuses. Convergence of people refers to large amounts of volunteers arriving at a disaster area, creating congestion in the system and even hindering the response (Barraket, Keast, Newton, Walters, & James, 2013; Kendra & Wachtendorf, 2001; Tierney, 2003; Wachtendorf & Kendra, 2004).

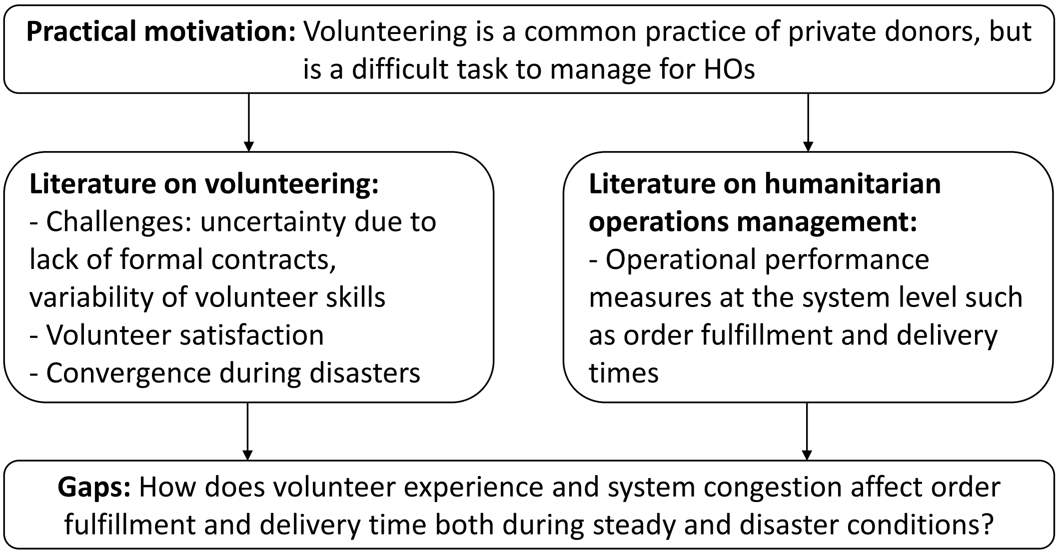
Most of the recent research about volunteer management studies how to keep volunteers motivated and satisfied with their tasks, because when volunteers are satisfied, they stay for longer periods of time, are more likely to also donate financially to the organization and recommend the volunteer experience to family and friends (Wisner et al., 2005). Researchers have studied enhancers of volunteer satisfaction such as schedule flexibility, training, empowerment, recognition, social interaction and economic rewards (Lacetera, Macis, & Slonim, 2014; Wisner et al., 2005). They have also considered how to use labor assignment to match volunteers' skill levels and preferences with the requirements of the HO and beneficiaries (Falasca & Zobel, 2012; Falasca, Zobel, & Ragsdale, 2011; Lassiter et al., 2015; Sampson, 2006). In addition to match volunteer preferences, this last work on labor assignment has also included how to improve the performance of HOs by using scheduling and training in an attempt to minimize possible future organizational costs, reduce volunteer labor shortage and minimize unmet task demand (Falasca & Zobel, 2012; Falasca et al., 2011; Lassiter et al., 2015; Sampson, 2006).

This review of the literature on volunteer management shows that most studies are concerned with understanding how to motivate and satisfy volunteers with their task assignments and job design. However, only few of these models consider that volunteers may not have the required skill set to complete a task (Lassiter, Alwahishie, & Taaffe, 2014; Lassiter et al., 2015). Other studies consider the challenges of volunteer convergence during disasters. However, this research usually takes a descriptive approach, because it is difficult to collect operational data about the consequences of convergence and system congestion under pressing circumstances.

A focus on volunteer satisfaction in combination with a descriptive approach makes it difficult for researchers to study systematically different operational tactics to manage volunteers and evaluate the implementation of those tactics on the performance of the overall system. An alternative approach would be to consider other challenges related to volunteers such as uncertainty or experience, and study them under more operational lenses, considering both empirical data and system performance measures such as order fulfillment and delivery times.

There is an opportunity to advance the research in volunteer management by building on past research. First, from a methodological perspective, authors interested in understanding volunteerism could combine some of the considerations of previous mathematical models with empirical data to validate and extend their findings. Second, from a conceptual perspective, authors can consider mixing volunteer characteristics (e.g., volunteer uncertainty, experience, learning) with system features (e.g., congestion) and study their effects on operational performance measures of HOs such as order fulfillment and delivery times. Possible research avenues on this stream are *how does volunteer uncertainty affect order fulfillment and delivery time in steady charity operations? How does volunteer experience affect order fulfillment and delivery time during disaster response operations? How does congestion affect order fulfillment and delivery time during disaster response operations? What are the best policies to manage congestion?* Figure 1.3 summarizes my arguments.

Figure 1.3 Summary diagram on managing time donations from private donors



1.6. Dissertation Structure and Contribution

This dissertation is composed of three studies addressing some of the questions about humanitarian funding posed in the subsections above. The goal is to show that HOs do not always have a passive role in the donations process. Instead, the main contribution of this dissertation is to propose that HOs can have an active agency in this process by following strategies to access and manage donations from both institutional and private donors. This contribution is split in three chapters. Chapter 2 draws on resource dependence theory (RDT) to investigate the strategies that HOs follow to have access to financial resources from institutional donors. Chapter 3 looks into the use of new channels such as crowdfunding to raise individual donations and the way HOs can potentiate online crowdfunding campaigns using transparency. Chapter 4 considers operational policies to manage individual time donations, i.e. volunteers, in the case of a charity storehouse. Finally, Chapter 5 summarizes the main findings and conclusions from the empirical studies of this dissertation.

Chapter 2, *"In Need of Aid: Funding Uncertainty and Diversification in Humanitarian Operations"* is a working paper co-authored with Sebastian Villa and Eric Quintane. This chapter studies how HOs tackle the uncertainty they face when accessing funding from institutional donors using a RDT perspective. Funding for humanitarian operations fluctuates over time and for each type of disaster (Tomasini & Van Wassenhove, 2009), which makes the funding process highly uncertain for HOs (Burkart et al., 2016). According to RDT, HOs should respond in a strategic way to reduce this uncertainty and secure the financial resources required to run their operations (Aldrich, 1979; Emerson, 1962; Pfeffer & Salancik, 1978). The aim of this paper is to investigate the strategies that HOs follow to reduce uncertainty when accessing financial resources and how these strategies influence other managerial decisions such as diversification.

We propose that HOs follow two strategies: finding alternative sources of funding and developing long-term relationships with donors. We argue that while finding additional sources of funding reduces *current* uncertainty and enables survival, it decreases the organization's capacity to diversify (i.e. to venture into new service sectors and geographical regions) because it does not reduce *future* uncertainty. Building on the concept of relational embeddedness, we propose that an alternative strategy – developing long-term relationships with donors – not only increases survival but also reduces future uncertainty and facilitates diversification. We test our hypotheses by using information from over 30,000 donations provided by 222 donors to 845 HOs during 1999-2016

This chapter contributes to two streams of literature: humanitarian funding and RDT. First, we extend the discussion on humanitarian funding by acknowledging the agency HOs have in the funding process. Past research on funding has assigned a passive role to HOs giving the entire power over the process to donors, even when HOs can unilaterally decide which donors to reach. This approach is problematic, because it leaves HOs in a helpless situation and completely dependent on donors' will. Instead, we show that HOs have an active role during the grant application process. Second, we add to the recent interest in a dynamic view of RDT, by considering the role of time in relations and examining the consequences of strategic actions on other managerial decisions of organizations. We apply the role of time to uncertainty and distinguish between *current* and *future* uncertainty, which enables us to specify the effect of relationship duration on reducing uncertainty and increasing diversification. Furthermore, our work contributes to the understanding of the consequences of strategic actions by showing that the strategies organizations follow to reduce uncertainty and access resources have different effects on their ability to diversify. We suggest that highly dependent organizations can choose their strategies not only to survive, but also with the objective to ensure their future diversification.

Chapter 3, *"Transparency in Crowdfunding for Emergency Management"* is a working paper co-authored with Jorge Mejia and Alfonso Pedraza-Martinez. This chapter studies how HOs can potentiate the new channel of online crowdfunding platforms to access funding from individual donors. HOs are expanding the channels they use to reach out for funding in order to increase their donor bases and respond to growing needs. The $30 billion online crowdfunding market is one of such new channels (Barnett, 2015). For example, the American Red Cross regularly uses crowdfunding campaigns in platforms to fund disaster response operations.

Crowdfunding campaigns can use two transparency tools to increase the trust of potential donors and subsequent donations: certification and updates. Certification is a form of conventional transparency that ensures the campaign is benefiting a charity organization, which fully discloses legal and financial information to the government. Updates are additional status posts or messages that the organizer issues after launching the campaign and are a form of operational transparency when they communicate the campaign's work to potential donors. Using over 100,000 campaigns from a large crowdfunding website, we uncover specific conditions under which the two forms of transparency increase donations. Our results show that both certification and updates have a positive effect on donations per month. Interestingly, work-related updates (operational transparency) have a stronger effect on increasing donations than certification (conventional transparency).

This chapter contributes to research in funding for humanitarian operations as well as transparency. We extend the current research on funding in two ways. First, we consider crowdfunding as a new channel to raise funds for emergency relief, which has not received attention in the humanitarian funding literature. Second, we add to established literature which states that private donors do not care about operational performance. We show that private donors pay attention to transparency and the work performed during emergency operations when making donation decisions. We contribute to the literature in transparency by comparing two types of transparency: conventional and operational transparency. We show that in a setting that requires fast responses, such as emergencies, operational transparency (via work-related updates) increases donations more than conventional transparency (via certification). Our findings also have managerial implications for individuals and organizations aiming to leverage online crowdfunding campaigns for emergency management. Certified organizations can have a bonus on donations by including work-related updates in their crowdfunding campaigns. Non-certified individuals and organizations can compensate for their lack of conventional transparency by adding work-related updates to increase donations.

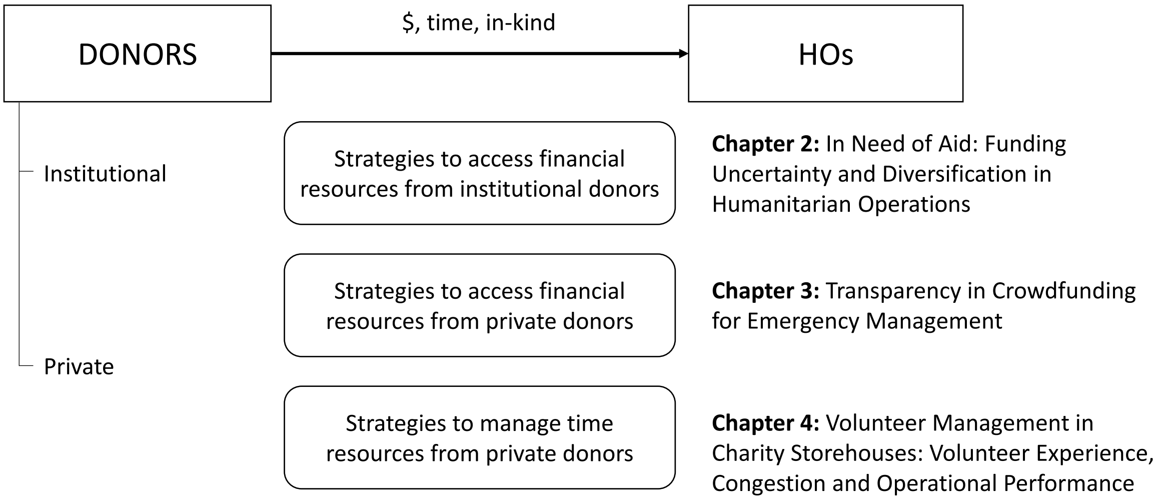
Chapter 4, *"Volunteer Management in Charity Storehouses: Volunteer Experience, Congestion and Operational Performance"* is a working paper co-authored with Alfonso Pedraza-Martinez and Maria Besiou. This chapter studies the way HOs can potentiate time donations from individual donors. One of the important resources for HOs is the support they receive from private donors. Individuals do not only donate money but also time to support humanitarian action and their donations are not negligible. However, properly volunteer management can be difficult for HOs, due to the high uncertainty related to volunteer experience and the challenges posed by system congestion.

In order to understand better these different challenges, we study volunteer management at a large faith-based organization that operates a charity storehouse, in which the whole supply chain works exclusively with volunteers (from supply to delivery). We model the preparation of beneficiaries' orders by volunteers in the storehouse as a function of volunteer experience and congestion. We explore how operational decisions, such as the type of volunteers' pairing in teams and whether to allow or impede congestion, affect two performance measures: on-time order preparation and additional time to prepare the orders.

We use empirical data to build an agent-based simulation model to explore the drivers of on-time order preparation at the storehouse, and we design eight experimental treatments varying volunteer experience and congestion. First, we study a scenario under steady conditions in which the demand of the beneficiaries is known in advance and cannot be lost since volunteers will stay in the storehouse as long as needed to prepare all the orders. Then, we put the model through three different disaster conditions: (1) high demand, (2) high supply of volunteers and (3) high demand and high supply. We explore again the drivers of both performance measures at the storehouse level in order to understand the best policies to manage volunteer experience and congestion under these extreme scenarios.

This chapter contributes to the literature on humanitarian operations and volunteer management by moving away from research topics related to volunteer satisfaction and scheduling. Instead, the chapter shows boundary conditions for the effectiveness of policies to manage time donations that (i) allow collaboration between experienced and inexperienced volunteers and (ii) limit (but do not eliminate) congestion. To our knowledge, there are no operations management studies examining the effects of volunteer experience and congestion on the operational performance of humanitarian organizations. Figure 1.4 gives an outline of the empirical chapters (Chapters 2 to 4).

Figure 1.4 Outline of empirical chapters



Chapter 2. In Need of Aid: Funding Uncertainty and Diversification in Humanitarian Operations[1]

Abstract: Research on resource dependence focuses on the strategies dependent organizations follow to access resources in order to survive. In the humanitarian context, humanitarian organizations (HOs) depend on resources from donors and diminish their dependence by accessing multiple sources of funding. We argue that while finding additional sources of funding reduces *current* uncertainty and enables survival, it decreases the organization's capacity to diversify (i.e. to venture into new service sectors and geographical regions) because it does not reduce *future* uncertainty. Building on the concept of relational embeddedness, we propose that an alternative strategy – developing long-term relationships with donors – not only increases survival but also reduces future uncertainty and facilitates diversification. Using information from over 30,000 donations provided by 222 donors to 845 HOs during 1999-2016, we show that the strategies of finding alternative sources and developing long-term relationships have the hypothesized effects on the ability of organizations to diversify. Our results extend prior work by suggesting that highly dependent organizations can choose strategies in order to ensure not only their immediate survival but also their future diversification.

Keywords: funding, diversification, resource dependence, humanitarian organizations

[1] Paper co-authored with Sebastian Villa and Eric Quintane

2.1. Introduction

Humanitarian organizations (HOs) provide relief to vulnerable people using funds obtained from institutional (e.g., governments) and private (e.g., individuals or private companies) donors that support their operations. Obtaining funds is difficult and uncertain because there is high competition among HOs to get donations and the amount of available funding is not sufficient to cover all needs (Burkart et al., 2016; Lattimer et al., 2017). To manage the uncertainty of accessing available funds, HOs look for ways to secure a flow of financial resources from donors to run their operations. Resource dependence theory (RDT) (Pfeffer & Salancik, 1978) provides a natural conceptual framework to understand how HOs handle the uncertainty of resource flow from donors. RDT scholars have outlined potential strategies that highly dependent organizations may follow to overcome uncertainty and increase their chances of survival such as reducing the need for the resource, forming alliances or coalitions, or finding new partners (Beckman, Haunschild, & Phillips, 2004; Casciaro & Piskorski, 2005; Emerson, 1962; Katila, Rosenberger, & Eisenhardt, 2008). However, in the humanitarian context, the imbalance of dependence between HOs and donors implies that HOs can realistically only follow a strategy of finding alternative sources since they can neither reduce their need on financial resources nor form coalitions, given the strong competition for resources (Lindenberg, 2001; Van Wassenhove, 2006). When finding alternative sources, HOs ask for funding from multiple donors in order to maximize the probability of obtaining resources and to reduce the dependence on the unpredictable nature of an individual donor decision-making process.

The main argument of this paper is that while the strategy of finding alternative sources of funding enables HOs to acquire resources to survive, it does not reduce the uncertainty of obtaining resources in the future, which negatively impacts the diversification of HO's activities into new sectors or regions. Diversification is critical for HOs because this is how HOs gain visibility, experience and potentially increase organizational performance (Kim, Hoskisson, & Wan, 2004; Rumelt, 1982). Asking for funds from multiple donors does not reduce the uncertainty of obtaining resources in the future, because the funds obtained by HOs from donors are typically targeted to a specific crisis (Lattimer et al., 2017), which change from year to year. Hence, HOs need to constantly apply to grants, each of which does not guarantee long-term stability (Burkart et al., 2016; Natarajan & Swaminathan, 2014; Oloruntoba & Gray, 2006). This uncertainty about future funding creates an incentive for HOs to stay in the same region-sector of expertise, so that they can more easily use their experience to show effectiveness during the grant application process (Hyndman & McDonnell, 2009). This incentive affects negatively HOs' capacity to diversify their activities into new service sectors and new geographical regions.

Building on the concept of relational embeddedness, we propose that HOs that develop long-term relationships with their donors can reduce current and future uncertainty (Beckman et al., 2004; Uzzi, 1997) and, as a consequence, will be more likely to diversify their operations in new sectors or regions. A long-term relationship between a HO and a donor implies an increased opportunity of inter-organizational learning that reduce both current and future uncertainty (Gulati, 1995; Rogan, 2014; Rogan & Greve, 2015; Uzzi, 1997). Inter-organizational learning facilitates gaining access to new grants from the same donor because the HO learns how to write grants and how to report progress in a way that is customized to the specific requirements of the donor and also because the accumulated experience of the HO with the donor is more easily evaluated by the donor. This inter-organizational learning facilitates the diversification of activities of the HO into new sectors or regions because the flow of resources towards the HO is more secure, giving the organization flexibility to take additional risk, but also because the HO and donor can accompany each other when entering new sectors or regions.

To test our arguments, we analyze over 30,000 donations targeted to 845 HOs from 1999 to 2016. We collect the data from the Financial Tracking System (FTS), which is managed by the United Nations (UN) and reports donations based on grant application processes. For each donation, we identify the donor, the recipient HO, the funding amount, the service sector and the geographical region where the project develops. Based on the multiple interactions of HOs with donors, we create yearly measures of dependence and duration at the organization level. Given that we have data for HOs for several years, we structure the data as a panel to estimate our models. Panel data analysis allows us to track the evolution of HOs strategies over time while increasing the efficiency of our estimates and their representativeness. We use fixed effects in our models to control for HOs heterogeneity.

Results show that highly dependent organizations rely on the two strategies we identify to access financial resources for disaster-relief operations and survive: finding alternative sources of funding and developing long-term relationships with donors. We find that these strategies have different effects on the diversification approach of organizations. HOs with long-term relationships leverage on this stable flow of resources to diversify more by moving into new sectors and geographical regions. By contrast, the higher the number of alternative sources HOs develop, the less likely they are to increase the number of new geographical regions for their operations.

This study contributes to two streams of literature: humanitarian funding and RDT. First, we extend the discussion on humanitarian funding by acknowledging the agency HOs have in the funding process. Past research on funding has assigned a passive role to HOs giving the entire power over the process to donors (Besiou et al., 2012; Leiras et al., 2014; Pedraza-Martinez et al., 2011), even when HOs can unilaterally decide to which donors submit their proposals. This approach is problematic, because it leaves HOs in a helpless situation and completely dependent on donors' will. Instead, we show that HOs have an active role during the grant application process and they adopt different strategies both to access funding and to diversify their operations.

Second, we add to the recent interest in a dynamic view of RDT, by considering the role of time in relations and examining the consequences of strategic actions on other managerial decisions of organizations. Most research on RDT does not consider the role of time in shaping relationships. Here, we apply the role of time to uncertainty and distinguish between *current* and *future* uncertainty; an approach that also adds to recent efforts to identify among different levels of uncertainty (Beckman et al., 2004; Howard, Withers, Carnes, & Hillman, 2016) and enables us to specify the effect of relationship duration on reducing uncertainty and increasing diversification. Furthermore, our work contributes to the understanding of the consequences of strategic actions (see Rogan and Greve (2015)) by showing that the strategies organizations follow to reduce uncertainty and access resources have different effects on their ability to diversify. In particular, we suggest that highly dependent organizations can choose their strategies not only to survive, but also with the objective to ensure their future diversification.

2.2. Literature Review

When a disaster occurs, HOs deploy assets and human resources to help the most vulnerable population. In order for HOs to achieve this goal, they require financial resources given by donors. Donors give money to HOs in order to execute programs that will benefit people in need; i.e. donors pay for a service that they do not receive (Hyndman & McDonnell, 2009). This type of funding process characterizes humanitarian operations in contrast to commercial operations (Van Wassenhove & Pedraza-Martinez, 2012). Donors make funding available through grant applications. For instance, the Organization for

Economic Co-operation and Development (OECD) uses grant applications for 99.9% of the economic support given to emergency response for humanitarian assistance (OECD, 2017). To get these grants, HOs write customized proposals to donors. These proposals explain the use HOs will give to the funds, including information about service sector and geographical region, and evidence of their organizational strengths to run the project (e.g., experience in a sector or region). Usually different HOs apply for the same grants, creating competition among themselves and increasing the difficulty of getting donors' attention and support.

The high competition among HOs together with imperfect knowledge about the decision-making process of the donors make the grant application process inherently uncertain. Therefore, HOs face funding uncertainty permanently, which is both current and future. Current uncertainty arises from the difficulty of getting funds to respond to an imminent disaster. In these situations, HOs need to raise large amounts of funds at short notice (Oloruntoba & Gray, 2006), without being sure if they will get the required funds on time (Natarajan & Swaminathan, 2014). Future uncertainty is related with the inability of HOs to secure funds in the long-term. Donations are volatile and unstable, which impedes the long-term planning of HOs (Burkart et al., 2016). Consequently, HOs rely on practices such as keeping excessive safety stocks of goods (Kunz, Van Wassenhove, McConnell, & Hov, 2015) or reducing costs in low funding years (Stauffer, Pedraza-Martinez, & Van Wassenhove, 2016) to cover in case future funding is not available.

Under these conditions, theory predicts that HOs will attempt to reduce uncertainty in order to get the required resources (Gulati & Gargiulo, 1999; Stearns, Hoffman, & Heide, 1987; Thompson, 1967). To understand what strategies HOs follow to manage uncertainty, we build on insights from RDT and relational embeddedness.

2.2.1. Resource Dependence Theory

RDT studies the relationship between organizations and external stakeholders. In particular, RDT is concerned with how organizations can reduce uncertainty derived from the dependence on those who provide necessary resources for organizational survival (Hillman et al., 2009). As HOs need financial resources provided by donors to run their operations, we focus on understanding what strategies HOs follow to reduce dependence on donors and thus, manage the current uncertainty of accessing the required financial resources for survival.

Studies on the relationship between HOs and donors have mostly focused on earmarking and the active and constraining role of donors when giving donations, while considering the role of HOs as a rather passive one (Aflaki & Pedraza-Martinez, 2016; Besiou et al., 2012; Burkart et al., 2016). However, according to the principles of RDT, under situations of high dependence HOs may respond in various strategic ways to reduce uncertainty and access the required resources for survival (Aldrich, 1979; Emerson, 1962). Strategic actions can be categorized as unilateral or bilateral (Casciaro & Piskorski, 2005). Unilateral actions reduce the dependence of one organization on a stakeholder (Emerson, 1962). Bilateral actions focus on balancing the power by aiming directly at the constraining stakeholder (Davis & Cobb, 2010; Dieleman & Boddewyn, 2012; Drees & Heugens, 2013; Hillman et al., 2009; Pfeffer & Salancik, 1978; Wry et al., 2013). Bilateral strategies, such as mergers and acquisitions, are successful only when both organizations are mutually dependent (Casciaro & Piskorski, 2005), which is not the case in the HO-donor relationship because HOs are more dependent on donors than donors on HOs. Therefore, HOs rely on unilateral strategies to restructure their dependence relationships.

Unilateral strategies may reduce the dependence of HOs in three ways: by reducing the interest or need on the specific resource, by forming coalitions or by increasing the network of possible resource providers (Emerson, 1962; Froelich, 1999; Nienhüser, 2008). In our setting, HOs cannot renounce to the financial resources because they are essential for organizational survival and it is unlikely that HOs will form coalitions, given the strong competition for resources (Lindenberg, 2001; Van Wassenhove, 2006). Therefore, the only unilateral strategy available for HOs is finding alternative sources of funding. Increasing the number of donors not only reduces dependence but also helps manage uncertainty (Pfeffer & Salancik, 1978; Thompson, 1967). HOs can apply this strategy during the grant application, because they can decide to how many different donors to apply. Thus, HOs can reduce their dependence on a specific donor and current uncertainty to access funding for survival, by applying and receiving grants from multiple donors.

Hypothesis 1: *The greater the dependence of a HO on one or few donors, the greater the likelihood that the HO will increase its number of donors in the next year.*

2.2.2. Relational Embeddedness

The choice of strategies available to organizations also need to consider dynamic processes (Nelson & Winter, 1982). The work of Gulati (1995) and Gulati and Gargiulo (1999) suggest that organizations form ties to access critical resources and these relationships evolve in such a way that there is a greater accumulation of ties between increasingly embedded organizations. However, most past studies of resource dependence have temporally aggregated the resource-dependent relations (for exceptions see Rogan & Greve (2015) and Kitts et al. (2017)) and this aggregation can hinder a deeper understanding of the dynamic interactions of resource exchange. Particularly, we are interested in the role of repetitive interactions, or long-term relationships, as a strategy HOs use to reduce the uncertainty of accessing funding.

We argue that highly dependent HOs can reduce current uncertainty by developing long-term relationships with donors (Beckman et al., 2004; Gulati, 1995; Uzzi, 1997). As a HO applies to grants from the same donor, it develops organizational knowledge, routines and capabilities that become specific to the grant application process of this donor. This interorganizational learning process operates beyond the grant application. It also facilitates the interactions between the HO and the donor during the execution of the grant and at the closing stage of the process, which corresponds to the reporting HOs do to fulfill the accountability requirements from donors. This increased frequency of interactions help develop trust and cooperation, increase inter-organizational embeddedness and establish stable long-term relationships (Coleman, 1990; Gulati, 1995; Rogan, 2014; Uzzi, 1997). Therefore, we expect that when HOs are under conditions of high dependence and uncertainty, they do not necessarily choose to reduce dependence. Instead, HOs can build on that dependence to develop embedded relationships with donors and in this process, HOs are able to manage current uncertainty by securing a flow of resources from long-term donors.

Hypothesis 2: *The greater the dependence of a HO on one or few donors, the greater the likelihood that the HO will develop long-term relationships with its donors.*

2.2.3. Diversification

We conceptualize diversification as the incursion of HOs into new service sectors and new geographical regions. By diversifying their portfolio of operations, HOs can obtain informational and learning benefits (Beckman & Haunschild, 2002; Granovetter, 1973; Urrea, Villa, & Gonçalves, 2016) and send a positive signal of their competence to other stakeholders (Rao & Sivakumar, 1999). Hence, diversification can be critical for HOs to improve their operations and gain donor visibility. However, not all HOs are able to venture into new services or regions. We propose that the ability of HOs to diversify depends on the type of strategy used to access resources, because finding alternative sources of funding and developing long-term relationships have different implications for current and future uncertainty.

Finding alternative sources of funding is a strategy that allows HOs to reduce dependence on a single donor. In doing so, this strategy reduces the current uncertainty of survival but not the future uncertainty of accessing funding in the long term. Considering that the objective of the grant application process is to provide funds for a specific disaster (Lattimer et al., 2017), HOs that follow a strategy of increasing their pool of donors can increase the likelihood of getting funding for their current operations. However, as the availability of funds is highly related to the type of crisis and its visibility on the media (Aflaki & Pedraza-Martinez, 2016; Chandes & Paché, 2010; Scarpin & De Oliveira Silva, 2014), funding for humanitarian operations becomes highly variable over time (Burkart et al., 2016; Natarajan & Swaminathan, 2014; Oloruntoba & Gray, 2006). The fluctuating nature of the grants makes unlikely that HOs following a strategy of finding alternative sources can get long-term stability and thus, will still face high future uncertainty.

We argue that HOs facing high future uncertainty are discouraged from embracing the additional risk derived from venturing into new sectors and regions. For HOs, the main source of uncertainty is the access of funding for the survival of their current operations. To reduce the current uncertainty, a HO can follow a strategy of finding alternative sources and submit proposals to several donors. However, in order to increase the likelihood to receive the grants, these proposals should be targeted to the same service sector and geographical region in which the HO already has experience. During the grant application process, donors evaluate the previous performance and effectiveness of HOs before giving money to them (Aflaki & Pedraza-Martinez, 2016; Hyndman & McDonnell, 2009). Hence, a HO that builds on its experience can increase the possibility of getting funding from a new donor in the same sector or region of expertise. While writing proposals to venture into new sectors or regions, which are not aligned with previous expertise, could damage the ability of the HO to get funding for its current operations and survival. Thus, as HOs follow a strategy of increasingly finding alternative sources, we hypothesize that HOs will be less prone to diversify their operations.

Hypothesis 3: *The more a HO relies on a strategy of finding alternative sources of funding, the lower the likelihood that the HO will diversify by moving into new service sectors and geographical regions.*

By contrast, we argue that a strategy of developing long-term relationships increases diversification. When HOs and donors have worked together in the past and have established stable relationships, they are more able to learn how to successfully share information and develop common procedures to coordinate, which also increases their trust on each other (Keister, 2001; Uzzi, 1996). Moreover, given the inertia associated with embedded relations, long-term relationships can help mitigate risks and decrease the uncertainty of future exchanges (Bae & Gargiulo, 2004; Keister, 2001; Levinthal & Fichman, 1988; Powell, Koput, & Smith-Doerr, 1996; Rogan & Greve, 2015). Such a stable relationship secures current and future flow of resources for HOs, releasing the pressures imposed by both current and future uncertainty. That is, as HOs develop long-term relationships with donors, HOs not only reduce current uncertainty but also the future one. As uncertainty reduces, HOs become more flexible and able to absorb the additional risk derived from pursuing the parallel strategy of diversification. Thus, when HOs follow a strategy of developing long-term relationships, we expect that HOs will be more inclined to venture into new service sectors and geographical regions.

Hypothesis 4: *The more a HO relies on a strategy of developing long-term relationships with donors, the greater the likelihood that the HO will diversify by moving into new service sectors and geographical regions.*

2.3. Context and Data

There are two main databases that track donations to humanitarian operations. The first one is the Financial Tracking System (FTS), managed by the UN's Office for the Coordination of Humanitarian Affairs (OCHA). FTS has collected over 100,000 donations targeted to humanitarian operations from 1999 to 2016. FTS collects information about donations from governments, private donors, NGOs', and international agencies to different relief operations worldwide. The second one is the Organization for Economic Co-Operation and Development (OECD), which tracks and measures the flow of donations in order to ensure that funds are provided when, where and how they are most needed. The OECD database contains a representative sample of the donations made by Development Assistance Committee (DAC) countries. To test our hypotheses, we use data from FTS because FTS provides information at the donation level that is not included in such detail in the OECD data on Humanitarian Assistance. Using the FTS data is well suited for the analysis that we undertake here. First, FTS provides information about the organization that receives the donations. This aspect is relevant in our research because we are interested in understanding the strategic process of recipient organizations, while the OECD only provides information about the recipient country, ignoring the role of the implementing organization. Second, OECD only contains information from about 40 donor countries or organizations, while the

FTS has recorded information from more than 900 multilateral and private donors, providing a better worldwide coverage that we can explore in our empirical section. Third, FTS data collects information regardless the level of development of the affected country, offering a much broader view of socioeconomic levels of the recipient countries. Finally, FTS provides individual and up-to-date information and exact donation dates for each donation per organization, which allows us to identify aid flows and interaction dynamics, while the OECD database provides annual information, which is only updated every 2 years.

While the FTS data is based on a voluntary donor reporting, the magnitude of the amounts of funding reported to emergency aid is comparable to those reported by the OECD system (Fink & Redaelli, 2011; Raschky & Schwindt, 2012). To analyze the representativeness of our data, we compare the amount of money donated to unique regions reported by the FTS and OECD to humanitarian assistance from 2007 to 2016, which is the period in which OECD data is available. A simple comparison between both databases shows that FTS database reports a 22.3% higher amount of donations compared to OECD database. In addition, to test whether there are any differences in how these donations are allocated between both databases, we identify whether there is a difference in allocation between geographical regions in the two databases. Figure 2.1 shows no significant differences (p-value=0.99). For instance, Sub-Saharan Africa and Western Asia are the two regions with the highest donor attention in both databases.

2.3.1. Data and Descriptive Statistics

We collect FTS information from 963 donors that give on average USD 1.2M per donation, from 1999 to 2016. The range of the value of donations is bimodal: 63% of donors donate less than USD 1 million, while 25 donors donate over USD 1 billion during this period. The total number of recipient organizations is 3535. Similarly, 58% of these organizations receive less than USD 1 million in donations, while 3 organizations receive over USD 10 billion. Donations are distributed among projects in 12 different sectors (e.g. water and sanitation, health, education, emergency shelter, food security, logistics) and 17 different geographical regions (e.g. Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Northern Africa, Sub-Saharan Africa). Donors support on average 3.2 sectors and 2.6 regions.

Figure 2.1 Proportion of donations reported by the FTS and OECD to humanitarian assistance by region

From the 3535 HOs in the data, 1466 HOs (41.5%) receive only one donation while 32 HOs (0.9%) receive more than 500 donations. For instance UNICEF received 11933 donations over 18 years. For our analysis, we focus on organizations that receive more than 5 donations and less than 500 donations over the period of 1999 to 2016 for two reasons. First, we exclude HOs with less than 6 donations because we are interested in understanding the strategies HOs follow over time to successfully access resources, and organizations with very few donations do not provide enough information to be studied. Second, we exclude HOs with more than 500 donations. These are large HOs such as UNHCR, UNICEF, WFP, Red Cross Red Crescent Societies and Médecins sans Frontières. Large organizations can offer intangible resources to donors such as high-status, reducing the dependence of these

HOs on a particular donor (Casciaro & Piskorski, 2005; Emerson, 1962) and becoming more attractive to other potential donors (Rogan & Greve, 2015). Therefore, large HOs are likely to maintain long-term relationships with donors while avoiding strong dependence. After the exclusion of these observations, we end up with 845 HOs (23.9%) for our analysis. The 845 HOs receive an average of 37.7 donations from 222 different donors over the period of 1999 to 2016. The average amount of money per donation for these HOs is 1,28M USD. In addition, the 845 HOs develop projects on average in 4.80 different sectors and 4.03 different regions.

2.3.2. Measures

Dependent variables. We use three types of dependent variables to operationalize the strategies that HOs follow to access resources.

Alternative sources (AltS): Previous research on nonprofit organizations has considered alternative sources of funding as separate streams coming from government, private companies, individuals or commercial activities (Froelich, 1999; Frumkin & Keating, 2011). As we focus on the grant application process of HOs to institutional donors, we capture the strategy of finding alternative sources by considering the number of new donors giving funds to an organization in the same service sectors and geographical regions in which the organization has worked before. The dependent variable representing *AltS* for any given year is built as the interaction of the number of new donors giving funds to organization **A** for a recurrent service sector with the number of new donors giving funds to organization **A** for a recurrent geographical region in the same year. We use three steps to compute the number of new donors in a recurrent service sector (geographical region) in a given year. First, we identify the service sectors (geographical regions) in which each organization receives new donations in the current year. Second, we compare those service sectors (geographical regions) with the ones of the previous year. Third, we count the number of new donors giving to a service sector (geographical region) that has also received donations in the previous year. For example, let assume that organization **A** received donations from donors **D1** and **D2** in service sectors **S1** and **S2**, and in geographical regions **R1** and **R2** in the previous year. Now, let assume that in the current year organization **A** receives donations only in service sector **S1** from donors **D1** and **D3**, and receives donation in geographical region **R1** from donors **D2**, **D4** and **D5**. Therefore, organization **A** receives donations from new donors in service sector **S1** and geographical region **R1**. **S1** is a recurrent service sector for organization **A**, and the organization receives only from *one* new donor (**D3**). Similarly, **R1** is a recurrent geographical region for organization **A**, and the organization receives donations in this recurrent geographical region from *two* new donors (**D4** and **D5**). The final value of *AltS* in the current year is estimated by the multiplication of the number of new donors coming from the service sectors (1) with the number of new donors coming from the geographical regions (2). In this case, the final value of *AltS* for **A** in the current year is 2.

Duration (Dur). To convert the dyadic measure of relationship duration into an organizational measure, we use two steps. First, for each dyad in each year, we calculate the number of years that the relationship has been active during the last five years and divide it by five. This represents the percentage of time that the dyad has been active during the last five years. Second, we sum up all the dyadic percentages and divide them by the number of dyads that have been active. This final indicator varies between 0 and 1 and gives us information for each year about average proportion of active time of the organization that donors have been active as well. Let us give an example to see how this measure works. Let assume that organization **A** has been active for **5** years. During this time, it receives funds from donor **D1** in **4** years, and from donor **D2** only **1** year. Then to compute the duration measure, we first consider that the relationship **A-D1** has a duration or activity of 0.8 while

A-D2 has a duration of 0.2. Then, the average of relationship duration for **A** with its donors corresponds to 0.5. This means that the relationship of **A** with its donors have been active on average half of the time during the last five years.

Diversification: To operationalize diversification, we follow previous work that have used product-count and region-count measures (Hashai, 2015; Kim et al., 2004; Lubatkin, Merchant, & Srinivasan, 1993). In our case, however, as we do not have 2- or 4-digit SIC segments, we adapt our first measure of diversification as the number of new service sectors in which an organization is developing projects in a given year (*DivSec*). The second measure of diversification corresponds to the number of new geographical regions for which a HO receives funding each year (*DivReg*).

Independent variable. *Dependence (Dep).* Previous studies have used a variety of measures to account for dependence. Survey-based studies use items to capture dependence characteristics such as magnitude of exchange, concentration and degree of replaceability (Gulati & Sytch, 2007). Empirical studies have mostly followed Casciaro & Piskorski (2005), who use a measure that starts with interindustry flows of sales and purchases that is afterwards converted to business units (Casciaro & Piskorski, 2005; Xia & Li, 2013). However, our setting neither involve different industries nor bidirectional flow of resources. Therefore, building on the concepts of magnitude of exchange and concentration of dependence (Heide & John, 1988), we construct the measure of dependence as the Herfindahl-Hirschman Index (HHI) for all the donations an organization receives in a year. We normalize the index to be between 0 and 1 by dividing each value by 10000 (100^2) (Baker, 1990). A higher value of dependence indicates that the distribution of donations across donors is more concentrated, i.e. most of the donations received by the organization comes from one or few donors.

Control variables. We also control for the number of donors (*NumDon*) the organization has in the previous year. For the models explaining the number of new sectors (*NewSec*) and regions (*NewReg*), we also control for the number of sectors (*NumSec*) and regions (*NumReg*) in the previous year. We use organization fixed effects in the model to control for unobserved characteristics of HOs. As other available controls are not time-varying, we do not include them in the model. Table 2.1 presents descriptive statistics and correlation values for all variables.

Table 2.1 Descriptive statistics and correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7
1. Dependence	0.83	0.25	1.00						
2. Alternative sources	3.46	17.10	-0.32	1.00					
3. Duration	0.56	0.26	0.27	-0.14	1.00				
4. Number of donors	1.13	1.97	-0.76	0.63	-0.22	1.00			
5. Number of new sectors	0.50	0.85	-0.19	0.16	-0.19	0.18	1.00		
6. Number of new regions	0.39	0.77	-0.10	0.07	-0.09	0.10	0.42	1.00	
7. Number of sectors	1.11	1.54	-0.46	0.18	-0.06	0.50	0.54	0.25	1.00
8. Number of regions	1.02	1.43	-0.38	0.11	0.03	0.43	0.26	0.55	0.68

2.4. Model Specifications and Results

We run different panel data models with fixed effects to test our hypotheses, according to the four dependent variables. Equations (1) to (4) detail the four models.

$$AltS_{it} = \alpha + \beta * Dep_{i,t-1} + \gamma * NumDon_{i,t-1} + v_i + \varepsilon_{it} \quad (1)$$

$$Dur_{it} = \delta + \zeta * Dep_{i,t-1} + \eta * NumDon_{i,t-1} + v_i + \varepsilon_{it} \quad (2)$$

$$NewSec_{it} = \theta + \vartheta * \overline{AltS}_{i,t-1} + \lambda * \overline{Dur}_{i,t-1} + \mu * NumSec_{i,t-1} + v_i + \varepsilon_{it} \quad (3)$$

$$NewReg_{it} = \nu + \omega * \overline{AltS}_{i,t-1} + \sigma * \overline{Dur}_{i,t-1} + \rho * NumReg_{i,t-1} + \ v_i + \varepsilon_{it} \qquad (4)$$

where i indicates organization and t year, v_i represents the fixed effects by organization and ε_{it} represent the error term for each observation. $\overline{AltS}$ and $\overline{Dur}$ represent the standardization[2] of $AltS$ and Dur, respectively. We use the standardized version of the variables to make comparable the effects of the independent variables on equations (3) and (4). Given that in models 1, 3 and 4 we have count variables as dependent variables and the number zero has a high frequency, we use a negative binomial panel data approach to estimate these models. For model 2 we use a simple linear regression panel data approach.

Table 2.2 summarizes the results of the different panel data models. Model 1 has the alternative sources as dependent variable and hence provides evidence of the strategy followed by HOs to reduce dependence from donors. We find a positive and significant effect of dependence on finding alternative sources, which means that the greater the dependence of a HO on few donors, the greater the likelihood that the HO will increase its number of donors in recurrent sectors and regions the next year, controlling for the number of donors this year. This result gives support to hypothesis 1.

In Model 2, we account for the effect of dependence on the average duration of HO's interactions. We use the number of donors in the previous year as a control variable. We find that this variable has no effect on the duration strategy of the organization. Model 2 shows that the dependence has a positive and significant effect on the average duration. Therefore, the greater the dependence, the more likely the HO will develop long relationships with its donors. This result supports hypothesis 2.

Models 3 and 4 provide evidence of the diversification strategy followed by HOs. Model 3 has the number of new service sectors as dependent variable, while Model 4 has the

[2] We subtract the mean and divide by the standard deviation of each variable, so that the standardized variables have zero mean and unit variance

number of new geographical regions as dependent variable. Results show that there is a positive and significant effect of duration on both diversification strategies of HOs, such that the greater the average duration of a HO with its donors, the higher the likelihood that the HO will move to new service sectors and geographical regions. This result gives support to hypothesis 4. However, the effect of alternative sources is different in Models 3 and 4. Model 3 shows that the effect of finding alternative sources on the diversification in new sectors is positive but non-statistically significant. Instead, Model 4 shows a negative and significant effect of finding alternative sources on the diversification in new regions, which indicates that the more donors a HO has in recurrent regions and sectors, the lower its tendency to diversify by moving into new regions. These results give partial support to hypothesis 3.

Table 2.2 Results from panel data models

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	AltS	Dur	DivSec	DivReg
Dependence	0.264** (0.123)	0.088*** (0.017)		
Number of donors	0.012 (0.011)	-0.001 (0.002)		
Alternative sources			0.023 (0.017)	-0.078* (0.042)
Duration			0.101*** (0.020)	0.155*** (0.022)
Number of sectors			-0.142*** (0.013)	
Number of regions				-0.241*** (0.015)
Constant	-0.813 (0.121)	0.530*** (0.017)	1.521*** (0.136)	2.418*** (0.240)
-LL	5,132.6	2,372.6	7,313.7	5,928.6
AIC	10,271.2	4,801.0	14,635.4	11,865.3
BIC	10,289.6	4,781.8	14,664.3	11,894.1

Standard errors are in parentheses
*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

Results confirm that there are two different strategies through which HOs access funding from donors. The first one is by finding alternative sources: HOs with high dependence will look for additional donors in recurrent sectors and regions; however, the diversification into new regions will decrease with an increase on the alternative sources. The second one is by developing long-term relationships: HOs with long-term relationships remain with the same donors and leverage on this stable flow of resources to diversify by moving into new service sectors and new geographical regions.

2.5. Robustness Checks and Additional Analyses

To test the robustness of our results, we evaluate our models using different thresholds in our data set as well as alternative measures. First, we change the lower and upper bounds of the number of donations required by organizations to be included in our analysis. For the lower bound, we use two data sets, one in which organizations receive 4 or more donations (*4+don*), and another one in which organizations receive 8 or more donations (*8+don*). For the upper bound, we use two additional data sets, one in which organizations receive 300 or less donations (*300-don*), and another one in which organizations receive 700 or less donations (*700-don*). Table 2.3 shows the results for our four models using these four data sets. The effect of dependence on alternative sources (Model 5) and on duration (Model 6) remains positive and significant for all the different datasets. The effect of duration on the diversification in new sectors (Model 7) and new regions (Model 8) is positive and significant. In Model 7, the effect of alternative sources on the diversification in new sectors is always positive and non-significant. Similarly, in Model 8, alternative sources has a negative and significant effect on the diversification in new regions. These results are consistent with the ones presented in the previous section.

Table 2.3 Panel data estimations for different data sets

	4+don	*8+don*	*300-don*	*700-don*	*Large HOs*
Model 5 (AltS)					
Dependence	0.281**	0.247**	0.229*	0.284***	-0.176
	(0.123)	(0.124)	(0.135)	(0.117)	(0.241)
Number of donors	0.013	0.012	-0.014	0.020**	0.003
	(0.011)	(0.011)	(0.015)	(0.010)	(0.003)
Model 6 (Dur)					
Dependence	0.087***	0.089***	0.095***	0.086***	0.037
	(0.017)	(0.018)	(0.019)	(0.017)	(0.026)
Number of donors	-0.001	-0.001	0.000	-0.002	-0.001**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
Model 7 (DivSec)					
Alternative sources	0.020	0.025	0.023	0.024	-0.044
	(0.017)	(0.017)	(0.017)	(0.017)	(0.067)
Duration	0.135***	0.072***	0.111***	0.099***	-0.072
	(0.019)	(0.021)	(0.021)	(0.020)	(0.044)
Number of sectors	-0.146***	-0.143***	-0.134***	-0.150***	-0.348***
	(0.013)	(0.013)	(0.014)	(0.012)	(0.025)
Model 8 (DivReg)					
Alternative sources	-0.068*	-0.086*	-0.072*	-0.061*	0.010
	(0.036)	(0.045)	(0.049)	(0.034)	(0.051)
Duration	0.155***	0.136***	0.159***	0.150***	0.089**
	(0.021)	(0.022)	(0.022)	(0.021)	(0.042)
Number of regions	-0.252***	-0.234***	-0.227***	-0.239***	-0.228***
	(0.015)	(0.015)	(0.017)	(0.014)	(0.021)

Standard errors are in parentheses
*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

In addition, we test our four models using only large HOs (*Large HOs*) in our analysis. We define large HOs as those organizations that receive 500 or more donations over the period of 1999 to 2016. Last column on Table 2.3 shows the results. Model 5 and Model 6 show a non-significant effect of dependence on alternative sources and on duration. These results are aligned with the fact that these organizations can offer intangible resources to donors thereby becoming more attractive to other potential donors (Rogan & Greve, 2015). Therefore, the dependence has no effect on likelihood of HO to increase the number of new donors or have long relationships. Models 7 and 8 show a non-significant effect of alternative sources on the diversification in both new sectors and new regions. Model 7 shows that the average duration has no effect on the diversification strategy in new service sectors, while Model 4 shows a positive and significant effect of duration on the diversification in new geographical regions. Therefore, for large HOs, duration is more likely to have an effect on the diversification in new regions than in new sectors.

Second, we evaluate the robustness of the effect of duration on our results. We change the measure of duration by varying the number of years that the relationship has been active. We consider three (3-years) and seven (7-years) instead of five years. Table 2.4 shows the results, which are consistent with the estimations provided in Table 2.2. Therefore, our findings are robust to different time intervals in the estimation of average duration.

Table 2.4 Panel data estimations for duration

	3-periods	7-periods
Model 9 (AltS)		
Dependence	0.265**	0.265**
	(0.123)	(0.123)
Number of donors	0.013	0.013
	(0.011)	(0.011)
Model 10 (Dur)		
Dependence	0.056***	0.081***
	(0.017)	(0.017)
Number of donors	-0.000	-0.005**
	(0.002)	(0.002)
Model 11 (DivSec)		
Alternative sources	0.026	0.022
	(0.017)	(0.017)
Duration	0.144***	0.087***
	(0.021)	(0.020)
Number of sectors	-0.157***	-0.139***
	(0.013)	(0.013)
Model 12 (DivReg)		
Alternative sources	-0.078*	-0.079*
	(0.042)	(0.041)
Duration	0.135***	0.165***
	(0.023)	(0.021)
Number of regions	-0.250***	-0.236***
	(0.015)	(0.014)

Standard errors are in parentheses
*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

Finally, we examine two mechanisms by which HOs diversify their activities: (1) HOs tend to apply to new sectors and regions funded by donors in the past and (2) recurrent donors provide increased support to the diversification strategy of HOs with whom they have long-term relationships. To test the feasibility of these mechanisms, we estimate HOs' tendency to get donations in new sectors or regions, which have been previously funded by donors. We assess whether this tendency is stronger for short- or long-term relationships. Initially, we identify the sectors (regions) in which donors gave donations in the previous period. Then, we identify the new sectors (regions) in which each HO receives donations from every donor in the current period. For each HO, we compute the proportion of new sectors (regions) that overlap with the sectors (regions) in which each donor gave donations in the previous period. We find that HOs have the tendency to apply to grants in new sectors (regions) previously supported by donors. Moreover, the average proportion of overlapped new sectors (regions) is higher for longer HO-donor relationships ($p<0.01$ for both sector and regions), which indicates that recurrent donors directly support the diversification strategy of HOs. Even if this is just one test and is not the main argument of our study, these results provide support to the proposed mechanisms to explain how HOs diversify their operations and receive support from long-term donors in these efforts.

2.6. Discussion

We identify two different types of strategies that HOs follow to reduce the uncertainty imposed by their high dependence on donors and to access funding. The first strategy consists of finding alternative donors in the same sector and region where the organization has expertise. The second strategy refers to developing long-term relationships with donors. We show that these strategies have different effects on the diversification efforts of HOs. HOs that strongly rely on finding alternative donors are less likely to diversify their operations in new sectors or regions, compared to HOs that mainly rely on developing long-term relationships with donors. We explain this difference on diversification by distinguishing between current and future uncertainty. While both strategies reduce the current uncertainty of accessing funds, only long-term relationships reduce future uncertainty. As HOs reduce future uncertainty by establishing a stable flow of resources from long-term donors, they obtain the flexibility needed to face more risk and move into new sectors and regions.

Our findings contribute to the literature on humanitarian funding. It is well established that HOs have to deal with high uncertainty, because they usually rely on grants that do not provide long-term stability (Burkart et al., 2016; Natarajan & Swaminathan, 2014; Oloruntoba & Gray, 2006). However, there is a lack of research on how HOs reduce uncertainty. In fact, most of the literature on humanitarian funding frames the donation process to be only under the control of donors (Besiou et al., 2012; Leiras et al., 2014; Pedraza-Martinez et al., 2011; Van Wassenhove, 2006). This approach is problematic, because it implies that HOs are helpless and fully dependent on donors' will. Instead, we show that the role HOs have during the grant application process is rather active: HOs adopt different strategies both to access funding and to diversify their operations.

This work also contributes to the literature on RDT in two ways. First, by adding the role of time, we differentiate between current and future uncertainty, and explain their link with strategies to reduce dependence. For instance, Lee, Mun & Park (2015) find that organizations that depend on one or few critical resource providers have a reduced likelihood to survive, compared to those organizations that follow a strategy of finding alternative partners. By adding the role of time, we are able to separate highly dependent short-term relationships from highly dependent long-term relationships (or embedded relations) and find the benefits of the latter. Moreover, we contribute to research on RDT that links strategic actions as a response to different types of uncertainty (Beckman et al., 2004; Howard et al., 2016). We add to this literature by (i) applying the role of time to uncertainty and distinguishing between *current* and *future* uncertainty and (ii) identifying the effect of relationship duration on reducing uncertainty and increasing diversification. Second, recent research on RDT considers a dynamic approach on how the strategic behavior that organizations follow to reduce uncertainty and dependence also influences other managerial decisions. Rogan and Greve (2015) examine the consequences after a pair of organizations decide to merge and find that common exchange partners respond by withdrawing from the relationship. We contribute to understanding the dynamics of RDT by studying the consequences of strategic actions on diversification. We show that highly dependent organizations can choose their strategies to access resources not only to survive, but also with the objective to ensure their future diversification.

There are two main limitations in our analysis, which are associated with the FTS dataset we use. First, the data and our results are limited to grant applications for humanitarian aid. That is, we do not capture other sources of funding such as support for development operations, individual donations or commercial activities to raise funds for non-profit causes (Froelich, 1999). These additional sources can be used by HOs that are either not included in our dataset or disappear after receiving few grants. Second, the FTS data include only voluntary reporting of both donors and HOs, which could lead to self-reporting biases. We mitigate this limitation by comparing our data with reports in other non-voluntary databases such as the OECD. As we do not find important differences, we expect that the potential biases do not significantly affect our findings.

Despite the limitations, our work opens the door for future research both in the same context and other settings. In the humanitarian context, we study the strategies of finding alternative sources and developing long-term relationships at the aggregated node level of the HO. Future work can study these and other strategies at the dyadic level of the donor-HO relationship or follow the opposite perspective of the donor to understand what policies (if any) donors consider in the funding process. Beyond the humanitarian context, we consider that our arguments can also extend to other business-to-business (B2B) settings in which it is difficult to develop bilateral strategies such as strategic alliances to secure future resources or in which solving current uncertainty does not necessarily solve future uncertainty. For instance, researchers have found that highly dependent satellite internet firms rely on the strategy of finding alternative sources (portals) to increase their web traffic and survival likelihood (S. H. Lee et al., 2015). As in our results, this strategy reduces current uncertainty; however, it is unknown what kinds of strategies satellite internet firms can use to reduce future uncertainty. Other settings are the markets for specialized products such as very exclusive wines or apparel designs, in which production is limited and long-term contracts between sellers and buyers are rare. In these cases, developing long-term embedded relationships is a good strategy for both sellers and buyers to reduce future uncertainty of exchange relations (Uzzi, 1997). Future research in B2B settings can consider how the strategies or mechanisms that mitigate one type of uncertainty can affect the other or, extending our work, how reducing one type of uncertainty can influence other managerial decisions such as diversification.

Chapter 3. Transparency in Crowdfunding for Emergency Management[3]

Abstract: Online crowdfunding has emerged as a powerful tool to raise cash for emergency relief. Crowdfunding campaigns can use two transparency tools to increase the trust of potential donors and subsequent donations: certification and updates. Certification is a form of conventional transparency that ensures the campaign is benefiting a charity organization, which fully discloses legal and financial information to the government. Updates are additional status posts or messages that the organizer issues after launching the campaign and are a form of operational transparency when they communicate the work of the campaign to potential donors. Using over 100,000 campaigns from a large crowdfunding website, we uncover specific conditions under which the two forms of transparency increase donations. Our results show that both certification and updates have a positive effect on donations per month. Interestingly, work-related updates (operational transparency) have a stronger effect on increasing donations than certification (conventional transparency). Therefore, individuals and organizations seeking to leverage online crowdfunding platforms can use work-related updates to increase donations above the certification effect or even to compensate for the lack of conventional transparency.

Keywords: humanitarian aid, crowdfunding, conventional transparency, operational transparency

[3] Paper co-authored with Jorge Mejia and Alfonso Pedraza-Martinez

3.1. Introduction

Humanitarian needs are growing faster than humanitarian funding (Besiou, Pedraza-Martinez, & Van Wassenhove, 2018). To increase their donor bases and respond to growing needs, individuals and humanitarian organizations are expanding the channels they use to reach out to potential donors for funding. The 30 billion dollars online crowdfunding market is one of the new channels (Barnett, 2015). For example, the American Red Cross regularly uses crowdfunding campaigns on online platforms to fund emergency relief. Moreover, crowdfunding platforms allow private donors to be better informed about the organizations to which they donate. Therefore, crowdfunding campaigns can also serve as a response to demands to improve transparency in emergency operations (Acimovic & Goentzel, 2016; Beamon & Balcik, 2008; Starr & Van Wassenhove, 2014). We investigate transparency in the content of online crowdfunding platforms and its effect on donations for emergency response.

We conceptualize transparency as the disclosure of information to external actors (Grimmelikhuijsen, Porumbescu, Hong, & Im, 2013; Hale, 2008) and compare two forms of transparency. The first is the conventional form of certification, which refers to the disclosure of legal and financial information of an organization to the government. The second, operational transparency, is about revealing information on the work or progress a campaign is making through updates to potential donors. Anchored in the transparency literature, we investigate three research questions: *(i) How does certification (conventional transparency) in crowdfunding campaigns affect donations for emergency relief?, (ii) How do work-related updates (operational transparency) in crowdfunding campaigns affect donations for emergency relief?, (iii) How does the effect of certification compare to the effect of work-related updates in donations for emergency relief?* To answer our research questions, we collect data about campaigns from a large online crowdfunding platform. Next, we describe the concepts and data that we use in our research.

Campaigns consist of an organizer, a purpose, a financial target and a timeline. Online crowdfunding platforms allow organizers (individuals or organizations) to create campaigns either for their own organization or on behalf of another person or organization (e.g., the American Red Cross), in order to raise money directly from a large pool of donors. The purpose justifies the campaign creation, which is then categorized according to different concepts defined by each platform. In our setting, organizers can categorize the campaign as medical, memorials, education, animals, and emergencies, among others. We focus on the "emergencies" category, which includes campaigns associated with earthquakes, fires, floods, storms, terrorism, tornadoes and tragedy (gofundme.com). For instance, organizers created crowdfunding campaigns after Hurricane Harvey in 2017 as well as Great Smoky Mountains wildfires and Hurricane Matthew in 2016. The financial target is the monetary goal that the organizer aims to achieve with the campaign. Finally, the timeline is the period in which the organizer expects to achieve the financial target.

Campaign organizers have the challenge of attracting potential donors and overcoming their natural lack of trust. Transparency is one mechanism through which organizers can increase trust (Buell et al., 2017). In the platform under study, organizers have two tools to show the transparency of the campaign: certification and updates. First, each campaign can fundraise for a certified or not certified charity. In our research context, to have a certified charity crowdfunding campaign, the organizer must represent a tax-exempt organization under section 501(c)(3) of the Internal Revenue Code. Organizations engaged in charitable activities, such as religious, scientific and educational organizations, may apply to the Internal Revenue Service (IRS) to obtain this status (IRS, 2018). The process of obtaining 501(c)(3) status may take months and requires the organization to be very transparent with the government. The organization must fully disclose the details behind the organization's charitable purpose, its operations, and the members of the organization. For example, the application process requires each charity to disclose compensation agreements, previous financial history, bylaws, and its members' potential conflicts of interest. Finally, to maintain non-profit status, the organization must meet annual report requirements that include detailed financial and operational information of the charity. As the literature identifies the disclosure of legal and financial reports to the government as a conventional mechanism for transparency (Edwards & Hulme, 1996; Hyndman & McDonnell, 2009), we categorize certification as a representation of conventional transparency. Therefore, when campaigns are marked as "certified," potential donors can be sure the organizers are transparent in disclosing information to the government. We expect this certification to increase donations compared to non-certified campaigns (Kraft, Valdés, & Zheng, 2017; Podolny, 1993; Rao, 1994).

Second, each campaign has the option to use updates to show transparency. Extant literature defines operational transparency as the action of revealing the work that is performed behind a service or system (Buell & Norton, 2011), which increases the perceptions of effort and trust from customers. Updates are additional status posts or messages that the organizer issues after launching the campaign to communicate with previous and potential donors. If updates communicate the campaign's work, they become a tool of operational transparency. As updates are written descriptions, we argue that words conveying work, action and transparency should communicate the progress of the relief efforts more effectively to existing and new donors. That is, when a campaign organizer makes the work that a campaign is doing "more salient," (Buell & Norton, 2011) the organizer engages in operational transparency. We argue that the increased operational transparency conveyed by the updates may lead to increased donations for the campaign.

To investigate the effect of transparency on humanitarian donations, we study one of the world's largest online platforms for charity crowdfunding. We collect data about updates and donations on all open campaigns (i.e., campaigns still receiving contributions) on the platform over a seven-year period (2010-2017). We observe over 1.1 million campaigns with 107,739 (approximately 10%) categorized as emergencies. For each campaign, we are able to identify the organizer, title, description, purpose, pictures, videos, financial target, creation date, amount raised, number of donors and updates (until the collection date). Approximately 51% emergency campaigns post at least one update in this time period. Moreover, we are able to identify the timeline of each update and donation, which we aggregate on a monthly basis, and whether the campaign is certified or not. Approximately 9% emergency campaigns are certified. To measure operational transparency, we use the Harvard General Inquirer (HGI), a well-established dictionary in text mining (Abrahams, Jiao, Wang, & Fan, 2012), and identify work-related words in each update. A panel constructed with our monthly data estimates the effects of conventional transparency (measured as whether the campaign is certified or not) and operational transparency (measured as the number of work-related words in the text of the update) on campaign donations in the platform.

Our results show that certification, or conventional transparency towards the government, has a positive effect on donations per month. Updates also have a positive effect on donations. However, not all updates have the same effect on donations. Donations increase significantly more when campaigns have work-related updates, or operational transparency, towards the donors. Interestingly, we find that the size of the positive effect derived from operational transparency is greater than the size of the effect of conventional transparency. In particular, each work-related word in updates increase donations on average by $65 per month, while being a certified campaign raises funds on average by only $22 per month. These results are consistent to different model specifications and survive multiple robustness tests.

Our work contributes to research in funding for humanitarian operations as well as transparency. We extend the current research on funding in two ways. First, we consider crowdfunding as a new channel to raise funds for emergency relief, which has not received attention in the humanitarian funding literature. Second, we add to established literature which states that private donors do not care about operational performance (Eftekhar, Li, Van Wassenhove, & Webster, 2017; Hyndman & McDonnell, 2009). We extend this literature by showing that private donors pay attention to transparency and the work performed during emergency operations when making donation decisions. We contribute to the literature in transparency by comparing two types of transparency: conventional and operational transparency. We show that in a setting that requires fast responses, such as emergencies, operational transparency (via work-related updates) increases donations more than conventional transparency (via certification). Our findings also have managerial implications for individuals and organizations aiming to leverage online crowdfunding campaigns for emergency management. Certified organizations can have a bonus on donations by including work-related updates in their crowdfunding campaigns. Non-certified individuals and organizations can compensate for their lack of conventional transparency by adding work-related updates to increase donations.

3.2. Literature Review

This research lies at the intersection of two streams of literature: funding and transparency in the humanitarian setting.

3.2.1. Funding in Humanitarian Operations

Burkart et al. (2016) highlight that funding is an important research area in humanitarian operations management. Funding in humanitarian operations can be in cash or in-kind (see Burkart et al. (2016) for a comprehensive literature survey). While in-kind donations are critical to humanitarian operations, these are not the focus of our research because crowdfunding platforms only take cash donations.

Extant literature on donations examines strategies organizations can use to increase donations. Kessler and Milkman (2016) use field experiments with the American Red Cross to find that priming donors' identity as previous donors by reminding them of their last donations increases new donations from past donors. Moreover, they find that identifying fundraising campaigns with names associated with generosity increase donations. Ryzhov et al. (2016) study a large data set on direct-mail communications between the American Red Cross and its donors during 2009-2011. They find that donor cultivation campaigns are more successful when they are informative rather than emotional. Aflaki and Pedraza-Martinez (2016) model an organization that faces a market of donors and find that offering donors the possibility of earmarking (i.e., donations for specific purposes) their contributions increases donations.

Humanitarian literature also examines the impact of funding, particularly earmarking, on operational performance. For instance, Pedraza-Martinez et al. (2011) study vehicle fleet management and propose that earmarked funding disincentivizes field programs to follow centralized fleet policies. Toyasaki and Wakolbinger (2014) use a game theoretical approach to model a humanitarian organization that acquires funding from a market of donors. They find that if an organization allows earmarking, fundraising costs decrease. Besiou et al. (2014) illustrate that earmarked funding causes delays on resource allocation during emergency response. Aflaki and Pedraza-Martinez (2016) find that by allowing some degree of earmarking, humanitarian organizations get a good balance between amounts of donations and operational flexibility. Lastly, Stauffer et al. (2016) report that temporary hubs provide humanitarian organizations some flexibility for the use of earmarked funds during emergency response.

Conversely, the impact of operational performance on funding has received less attention from the operations management community. Eftekhar et al. (2017) analyze data based on the media exposure and financial information of twenty-three humanitarian organizations. They empirically show that operational efficiency influences institutional donors, such as government agencies, but not private donors. Moreover, the effect of operational efficiency on donations has a delay, as current operational efficiency only influences future donations. Our research investigates the impact of transparency on humanitarian funding. We concentrate on crowdfunding, which is an unresearched fundraising channel where private donors (as opposed to institutional donors) provide earmarked donations to specific campaigns.

3.2.2. Transparency in the Humanitarian Setting

The study of transparency in humanitarian operations has been related mostly to accountability (Beamon & Balcik, 2008; Haavisto & Goentzel, 2015; Starr & Van Wassenhove, 2014; Villa, Odong, & Gonçalves, 2017). The two components of accountability are "the ability to know what an actor is doing and the ability to make that actor do something else" (Hale, 2008). Even if transparency only aims at the first component (what an actor is doing), it generates accountability (Fox, 2007; Hilhorst, 2002). Transparency is defined as "the availability of information about an organization or actor that allows external actors to monitor the internal workings or performance of that organization." (Grimmelikhuijsen et al., 2013) In this paper we are interested in understanding the effect of transparency on private donations in crowdfunding platforms. We study two types of information disclosed to different external actors. First, we consider conventional transparency as the disclosure of legal and financial information about the organization to the government. Second, we examine operational transparency as the publication of information about the campaign's work to individual donors. We compare the effects of both conventional transparency and operational transparency on the likelihood of organizations to receive donations from private donors.

3.2.2.1. Conventional Transparency

Scholars consider that conventional mechanisms for accountability and transparency are the disclosure of reports such as legal and financial statements (Edwards & Hulme, 1996; Hyndman & McDonnell, 2009). In the context under study, we define conventional transparency as the certification process through which organizers prove that the organization behind a campaign is a charity nonprofit, i.e. is registered as a 501(c)(3). We argue that if an organization is certified through this process, then the organization (and the campaigns associated to it) is transparent to the government. The basis of our reasoning is that transparency refers to openness and disclosure towards an external actor (Hale, 2008). Moreover, we define this certification process as conventional transparency because in order to earn and maintain 501(c)(3) status, organizations must disclose information fully to the government such as their purpose, operations, members, compensation agreements, previous financial history, bylaws and annual reports that include detailed financial and operational information (IRS, 2018). In fact, past research considers the 501(c)(3) status as a conventional mechanism for transparency (Ebrahim, 2005).

Transparency can bring benefits such as an improved usage of the donations, better service delivery to beneficiaries and more responsiveness (see Gaventa and McGee (2013) for a review). In supply chain contexts, increased transparency can also have economic benefits for organizations. For instance, Kraft et al. (2017) show that when companies are transparent about their social responsibility practices in its upstream supply chain, consumers are willing to pay higher prices for the company's products. Furthermore, the process to achieve conventional transparency, i.e. the certification process to become tax-exempt and receive 501(c)(3) status, can improve reputation and economic benefits to the organization (Podolny, 1993; Rao, 1994). We study the economic benefits of conventional transparency (i.e., governmental certification) in crowdfunding platforms.

3.2.2.2. Operational Transparency

Operational transparency is a relatively new concept in operations management. It emphasizes the importance to reveal the work behind a service in order to increase the customers' perceptions of effort and trust (Buell et al., 2017; Buell & Norton, 2011). The increased perception of effort and service value has been found in services with both short and long response times. Studies of services with short response times include self-service technologies and face-to-face services. In self-service technologies, Buell and Norton (2011) find that when a travel website shows the internal process of the search, users appreciate the value of the effort and are willing to wait longer times for service. Similarly, in face-to-face services, Buell et al. (2017) find that by introducing a visual connection between employees and customers, customers' perceived service quality increases by 22%. The authors explain that "seeing the work" is what increases appreciation of effort and, hence, quality.

The increased perception of effort also benefits services with long response times, such as services delivered by governments. Buell et al. (2016) find that when the government is transparent by "showing its work," it gains citizens' trust and benefits from citizens' engagement as information providers. The authors prove this relationship building on three different experimental studies. First, they use a computer simulation to show the activities the government performs. They find that after observing government activities, subjects increase their trust in the government. Second, the authors expose subjects to different types of service requests communication and the corresponding effort that government applies to address them. When communication is transparent, people also gain trust in and support for the government. The third experimental study with long response times uses a mobile phone application to request services from the government. Results show that in the transparent condition, in which subjects observe the response to their requests with a picture, users engage in submitting more subsequent requests and within more categories.

Long response times characterize online crowdfunding platforms. Response times are long because the campaign organizer can deliver the aid only when enough money has been raised. Moreover, organizers need to overcome the natural lack of trust of potential donors, who cannot know in advance whether crowdfunding campaign organizers will use the funds as promised (Gerber & Hui, 2013) and there are no enforcing mechanisms that donors can use to discourage organizers to deviate from the campaign objectives. Therefore, campaign organizers face the challenge of gaining the potential donors' trust in order to increase donations. We propose that in addition to using certification, organizers can communicate the work that is being done with previous donations and such an action can bring positive benefits to the campaign. In other words, when campaign updates are operationally transparent, they have the potential to increase trust, which should result in rewards for the organization (Buell et al., 2017, 2016; Buell & Norton, 2011).

Our paper contributes to two streams of research: funding in humanitarian operations and transparency. First, we extend the literature on humanitarian funding by studying crowdfunding as a new online channel that organizations and individuals can use to raise funds from private donors. We consider that private donors care about transparency and performance of emergency operations. Second, we extend the literature on transparency by comparing two forms of information disclosure: conventional and operational transparency. We study the effect of conventional transparency (via governmental certification) and operational transparency (via work-related updates) on donations for crowdfunding campaigns targeted to emergencies.

3.3. Context and Data

The crowdfunding platform we study enables any individual or charitable organization to raise funds to support social causes. The platform attracts over 40 million visitors per month and facilitates millions of dollars in campaign contributions. Since its foundation in 2010 to the end of 2016, the platform had raised over $4 billion dollars from over 50 million different users in 110 countries. These statistics reflect the high popularity of the platform and its growing influence in raising funds. For example, after the 2017 Las Vegas shooting tragedy, the platform raised over 11 million dollars, the highest amount ever raised for a single cause on a charity online fundraising platform.

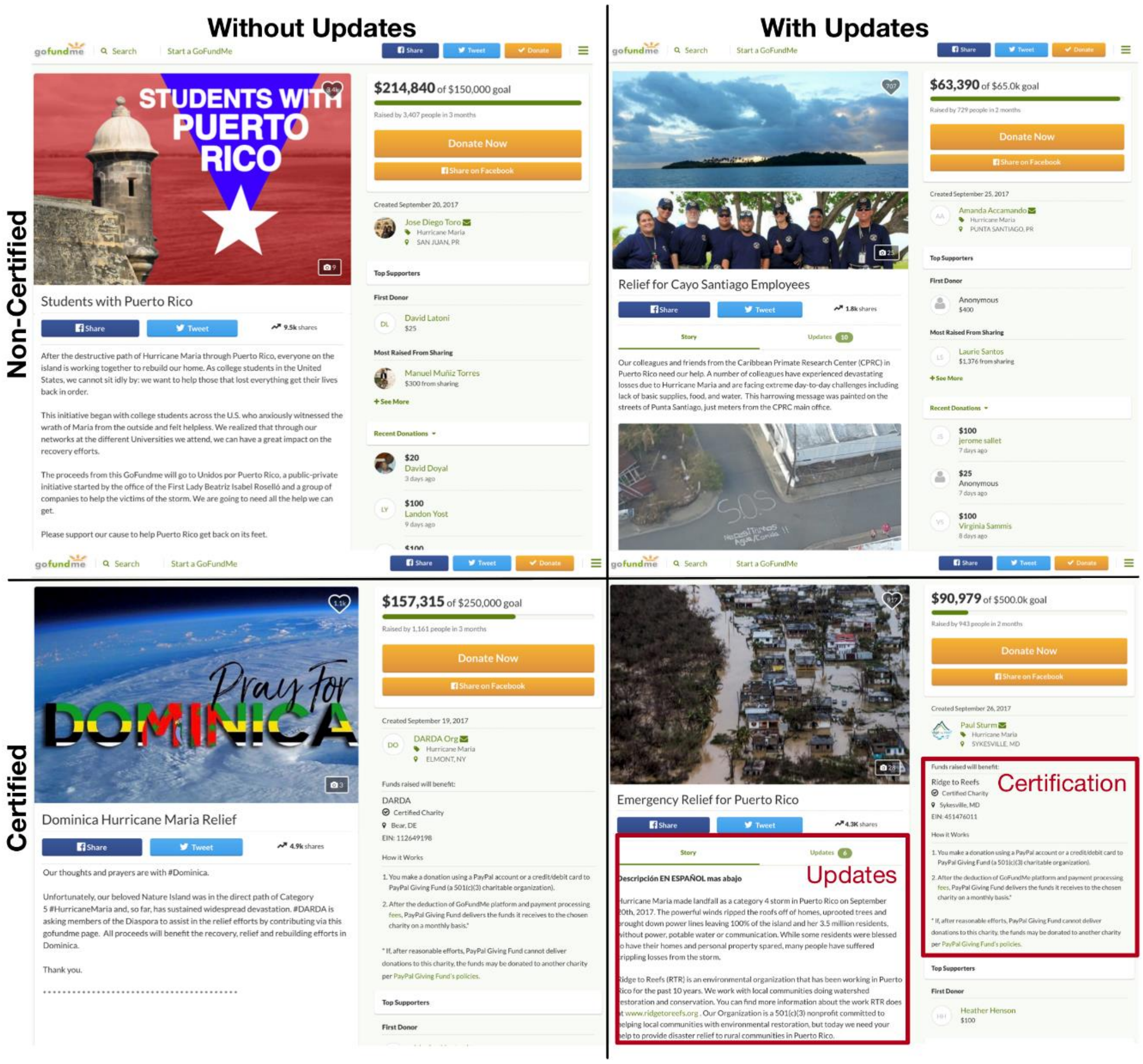
The platform allows the creation of fundraising campaigns for many needs from medical bills and emergencies to education, sports and animal welfare. When potential donors visit the website, they see the campaigns in order of popularity, along with filtering and sorting options (i.e., by category or by location). When organizers create a campaign, they must define a number of campaign characteristics. These characteristics include a written campaign description or “story,” explaining why organizers are raising money and how the funds will be used, multimedia content, such as images and videos, the beneficiaries of the campaign and whether it is fundraising for a certified charity, the duration of the fundraising campaign, and the amount intended to be raised. This amount is called the financial goal of the campaign and in our setting, it does not matter as much as in other kinds of crowdfunding platforms. Other crowdfunding platforms usually have a policy of “all or nothing,” which means that if the campaign does not reach the financial goal proposed, organizers cannot get any partial amount raised. However, in donation-based crowdfunding in general and in the platform under study, this policy does not apply. Even if the campaign does not reach the initial financial goal established, organizers can get any amount that has been donated.

There are two main tools to increase the trust of potential funders using transparency in the platform: certification and updates. First, the platform offers organizers the option to mark the campaign as a “certified charity,” which is only possible if the organization is tax-exempt under section 501(c)(3) of the Internal Revenue Code (IRS, 2018). Second, this platform offers organizers the option to create updates. Organizers post updates as the campaign progresses to allow users to track its advancement. These updates, much like the campaign descriptions, are made of text and multimedia content. Figure 3.1 presents a screenshot from our study context depicting four example campaigns for the relief efforts after Hurricane Maria in 2017. The campaigns on the right of Figure 3.1 display example campaigns with updates while the campaigns at the bottom of Figure 3.1 display campaigns that are fundraising for a certified charity. The focus of our study is the use of transparency in crowdfunding platforms both as certification and as work-related updates.

3.3.1. Data and Descriptive Statistics

We have data about updates and donations on 107,739 open emergency campaigns (i.e., campaigns still receiving contributions) on the platform over a seven-year period (2010-2017). We identify 9,804 certified emergency campaigns. Moreover, we observe that 55,477 emergency campaigns post at least one update in this time period. Before executing formal econometric analyses, we explore the relationship between donations and updates in a model-free environment. We use 22,820 campaigns that provide daily updates and information about donations. We examine the donations campaigns received five days before and after an update releases. Figure 3.2 shows evidence of a sharp increase in donations following an update. Thus, even without including campaign-level controls, there appears to be a clear temporal relationship between updates and donations with a surge of donations typically occurring the day of the update.

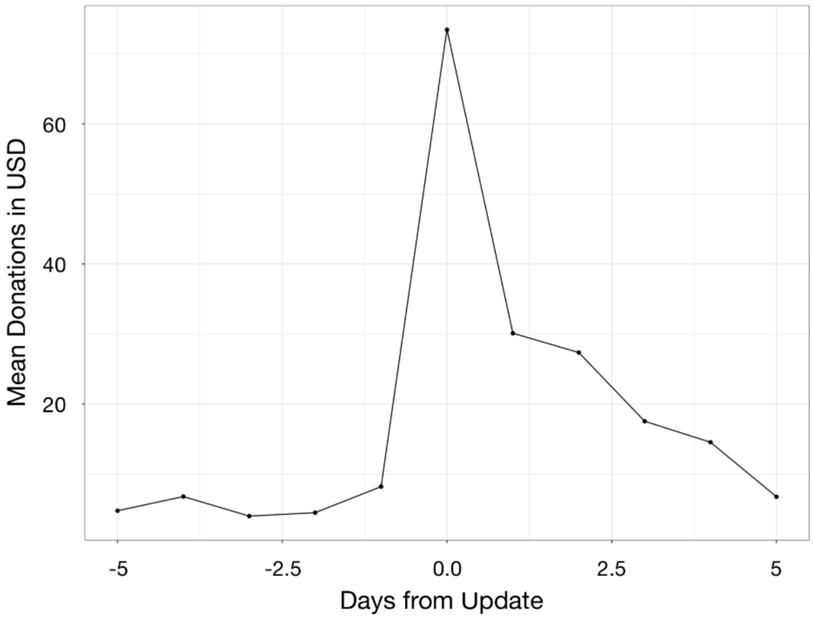
Figure 3.1 Comparing campaigns with updates and certification



3.3.2. Measuring Operational Transparency using Text Mining

In the management literature, there has been recent interest in analyzing textual information from the internet, particularly those related to social media platforms (Archak, Ghose, & Ipeirotis, 2011; Gopal, Marsden, & Vanthienen, 2011). For example, researchers have used user-generated content to measure the financial health of firms and markets (Antweiler & Frank, 2004; F. Li, 2010; Loughran & Mcdonald, 2011; Schumaker & Chen, 2009; Tetlock, Saar-Tsechansky, & Macskassy, 2008), to estimate and forecast customer preferences and choice (Cao, Duan, & Gan, 2011; Decker & Trusov, 2010; N. Li & Wu, 2010; Netzer, Feldman, Goldenberg, & Fresko, 2012), and to identify components and potential product defects across supply chains (Abrahams, Fan, Wang, Zhang, & Jiao, 2015; Abrahams, Jiao, Fan, Wang, & Zhang, 2013; Abrahams et al., 2012).

Figure 3.2 Average donations before and after an update



The process of extracting value from user-generated content online typically requires a series of steps to prepare unstructured data (preprocessing), extract semantic features, and use statistical models to link the extracted information to the variables of interest (Neuendorf, 2017; Shmueli, Bruce, & Patel, 2016). The objective of preprocessing steps is to focus on meaningful words by removing uninformative ones. With the text of the campaigns' updates, we follow standard preprocessing steps. Thus, we transform the text into lowercase, remove common words, such as "the," "and" and "of" and use Porter stemming to remove suffixes. To perform our analysis, we use the "tm" (text mining) package (Feinerer & Hornik, 2012) within R (R Development Core Team, 2000).

After preprocessing the text of the campaign updates, we utilize the Harvard General Inquirer (HGI) to extract information from each update. HGI is a well-established technique to extract semantic features from documents (Kelly & Stone, 1975; Stone, Dunphy, Smith, & Ogilvie, 1966). HGI counts the frequency of occurrence of concept classes, such as words reflecting the language of an institution (i.e., academic, religious, arts), words indicating motivation, or words echoing cognitive orientation.

Since our interest lies in identifying operational transparency in the text of campaign updates, we use the HGI class related to "socially defined ways of performing tasks or work." This class includes 261 words representing work actions such as "build," "clean," "equip" and "fix." We measure operational transparency as the count of work-related words because work-related words are the main means an organizer has to communicate the campaign's work. For example, if the text of an update contains: "We bought $150k worth of water and groceries: canned meats, soda crackers, rice, oil, mac&cheese, soups, etc. We also ordered 35 power generators and we filled 5 containers and shipped all this to PR," then we count four work-related words (i.e., "bought," "ordered," "filled" and "shipped").

After this procedure is complete, we have a numerical measure of frequency by which each campaign update describes its performing work or task. Considering that operational transparency increases trust and service value, which can also lead to increased future purchases (Gremler & Gwinner, 2000; McDougall & Levesque, 2000), we investigate whether work-related words in updates will raise future donations in crowdfunding campaigns. To account for the fact that some campaign updates contain more text than others, in our models we control for the total number of existing words in the update (i.e., word count).

3.3.3. Sentiment and Readability

As it is common in the text mining literature, we also control for other semantic characteristics existent in the text of the campaign and updates (Abrahams et al., 2015). First, we measure the sentiment of the text of a given campaign or update, that is, how positive or negative the content is. We use the HGI dictionary again to calculate the number of positive and negative words present in the text. Then, we calculate the sentiment score as the ratio of positive and negative sentences. By design this sentiment score must fall between 0 and 1, with 0 being more negative and 1 being more positive. Second, we measure the readability. We use the SMOG (Simple Measure Of Gobbledygook) readability index to measure the amount of cognitive effort needed to process the text (Ghose & Ipeirotis, 2011) . The SMOG index estimates the years of education needed to understand a document and has a range between 5 and 18; the lower the indicator, the more readable the text. We also calculate similar indices for sentiment and readability, such as QDAP (Qualitative Data Analysis Program), the Automated Readability Index (ARI), the Fog-Gumming readability index and the Coleman-Lindau readability index. The results obtained are fully consistent and are available upon request.

3.4. Model Specifications and Results

In order to conduct our analysis, we form an unbalanced panel dataset that aggregates the information of the campaign in a given month (e.g., the number of updates per month). This dataset also includes time-invariant variables, such as the financial goal of the campaign. Table 3.1 provides a list of variable definitions. Our dependent variable is the amount of donations in dollars for a given campaign in a time period (month). Our main independent variables are whether the campaign is certified, the number of updates for a given campaign in a time period and the number of work-related words in the update description. Table 3.2 provides descriptive statistics for each variable. We observe that the average monthly donation is $1,593.30, the average number of monthly updates is 3.71 and only about 9% of the campaigns are certified. In the models, we include time and location fixed effects to control for time trends, seasonal effects and any unobserved variables deriving from the place where the campaign is created. Additionally, we include all observable campaign-level and update-level characteristics, such as the multimedia content and shares in social media, as controls.

Table 3.1 Variable description

Variable	Definition	Type
Donations	Amount of donations for a campaign in USD	Dependent
Updates	Number of updates in a campaign	Independent
Certified	Binary indicator of whether the campaign benefits a certified charity	Independent
Work	Number of work-related words in the update description	Independent
N_images	Number of images in the campaign or update description	Control
N_videos	Number of videos in the campaign or update description	Control
Word_count	Number of words in the campaign or update description	Control
Sent	Average sentiment score in the campaign or update description	Control
Read	Average SMOG score in the campaign or update description	Control
Shares	Number of social media shares in the campaign description	Control
Faves	Number of times the campaign has been selected as a favorite	Control

Table 3.2 Summary statistics

Variable	Mean	Min	Max
Donations	1,593.30	0	10,980,200
Updates	3.71	0	201
Certified	0.09	0	1
Work	1.67	0	75
N_images	2.26	0	39
N_videos	0.10	0	21
Word_count	211.11	5	1,443
Sent	0.53	0.11	0.78
Read	9.17	5	12
Shares	36.20	0	990
Faves	27.01	0	710

We employ two models to address our research questions. In both models, the unit of analysis is campaign-time period, where time periods are one-month intervals. In the first model, we address the first research question and estimate the effect of certification and releasing updates on the amount of donations received in the same time period. This model includes all time points since campaign creation for all emergency campaigns in our dataset. The first model is:

$$Donations_{it} = \beta_0 + \beta_1 Updates_{it} + \beta_2 Certified_i + \gamma \boldsymbol{X}_i + \varepsilon_{it}, \qquad (1)$$

where $Donations_{it}$ is the dependent variable and refers to the amount of donations a campaign *i* receives during time period *t*. The independent variables of interest are $Updates_{it}$, the number of updates the campaign made in time period *t*, and $Certified_i$ that refers to whether the campaign i is a certified charity. $\boldsymbol{X}_i$ is a vector of all observable campaign-level covariates, which serve as controls, including the number of images and videos displayed in the campaign description, attributes of the text used to describe the campaign (word count, sentiment and readability) and the number of shares and favorites in social media. We employ robust standard errors, assume an exchangeable within-campaign correlation structure and use time and location fixed effects.

We display the coefficient estimates of model (1) in Table 3.3. We answer the first research question by finding a positive effect of certification of \$22.71 (*p<0.01*) on donations, which highlights the importance of conventional transparency to the government on the platform. In addition, we estimate that each additional update yields \$187.29 (*p<0.01*) in donations in the same time period. Moreover, we observe that the number of social media shares (\$9.93; *p<0.01*) and favorites (\$5.11; *p<0.05*) are also positively associated with donations, illustrating the role of social networks.

Table 3.3 Effect of campaign updates on crowdfunding donations for emergency relief

	Model 1.1: OLS		Model 1.2: AR(1)		Model 1.3: FE	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	376.97*	211.99	411.28*	249.03		
Updates	187.29***	71.05	185.94***	63.59	189.27***	67.49
Certified	22.71***	8.60	19.12**	7.98		
Campaign-level Controls						
N_images_camp	131.30	241.31	98.90	112.45		
N_videos_camp	36.43	59.60	49.23	39.76		
Word_count_camp	1.20**	0.51	1.98**	0.92		
Sent_camp	2.80	5.06	5.55	8.70		
Read_camp	0.01	0.05	0.07	1.89		
Shares_camp	9.93***	3.55	11.74**	5.01		
Faves_camp	5.11**	2.49	2.54*	1.51		
Fixed Effects						
Campaign Fixed Effects					Included	
Time Fixed Effects	Included		Included		Included	
Location Fixed Effects	Included		Included		Included	
R-squared	0.51		0.57		0.60	
Time periods (months)	51		51		51	
Groups (campaigns)	107,739		107,739		107,739	

*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

To assess the robustness of our results, we consider two different specifications and estimation procedures for model (1). First, we note that donations for a given campaign may be temporally autocorrelated. We, thus, also estimate model (1) assuming an autoregressive structure of order 1, AR(1), for the residuals. Second, while we include all characteristics of the campaign observable through the platform, certain unobservable characteristics may also be associated with donations, such as the financial health of the non-profit served by the campaign. Thus, we also estimate model (1) including campaign fixed effects to account for campaign-level differences. Table 3.3 reports both the AR(1) and fixed effects (FE) specifications. The coefficient estimates and significance are consistent across all specifications.

We use a second model to answer the second and third research questions. Conditional on a campaign having posted updates in a time period, this second model includes update characteristics and allows us to examine the effect of certification and work-related updates on the donations raised over time. Building on model (1) we add $Work_{it}$, the total number of work-related words appearing in updates of campaign *i* during time period t. We also include an interaction term between $Work_{it}$ and $Certified_i$, which indicates whether campaign *i* is certified, to understand whether certified charities benefit more or less from operational transparency,

$$Donations_{it} = \beta_0 + \beta_1 Work_{it} + \beta_2 Certified_i + \beta_3 Work_{it} Certified_i + \gamma \boldsymbol{X}_i + \alpha \boldsymbol{Y}_{it} + \varepsilon_{it}, \quad (2)$$

In addition to campaign-level controls in $\boldsymbol{X}_i$, model (2) includes update-level controls in $\boldsymbol{Y}_{it}$, such as the number of images and videos in the update and text characteristics (word count, sentiment and readability). We employ robust standard errors again, assume an exchangeable residual correlation structure and use time and location fixed effects. As in model (1), we also estimate model (2) assuming an AR(1) residual correlation structure as well as a model including campaign fixed effects (FE) to account for any unobservable campaign-level characteristics. Table 3.4 shows the estimated coefficients for all model specifications and p-values. Our results remain consistent across all specifications.

Table 3.4 Effect of campaign updates displaying operational transparency on crowdfunding donations for emergency relief

	Model 2.1: OLS		Model 2.2: AR(1)		Model 2.3: FE	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	323.32*	176.19	271.16*	156.99		
Work	65.27***	24.12	68.57***	23.13	71.46***	15.61
Certified	22.02***	6.11	20.57***	8.01		
Work*Certified	4.92**	2.14	5.01**	2.47	5.00**	2.09
Campaign-level Controls						
N_images_camp	93.19	216.89	101.87	199.77		
N_videos_camp	35.04	60.10	36.53	61.05		
Word_count_camp	1.59**	0.80	1.65*	0.99		
Sent_camp	2.00	5.06	2.80	5.06		
Read_camp	0.01	0.05	0.01	0.05		
Shares_camp	10.57***	4.01	9.63**	4.00		
Faves_camp	5.01**	2.40	5.11**	2.49		
Update-level Controls						
N_images_upd	10.68**	4.01	10.07***	3.42	11.42***	3.57
N_videos_upd	0.98**	0.40	2.11*	1.10	2.07*	1.21
Word_count_upd	3.39**	1.58	3.24***	1.20	2.80**	1.41
Sent_upd	3.04	6.65	3.80	3.06	4.17	7.02
Read_upd	0.01	0.05	0.01	0.00	0.01	0.01
Fixed Effects						
Campaign Fixed Effects					Included	
Time Fixed Effects	Included		Included		Included	
Location Fixed Effects	Included		Included		Included	
R-squared	0.55		0.56		0.66	
Time periods (months)	51		51		51	
Groups (campaigns)	55,477		55,477		55,477	

*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

From the first specification of model (2), we answer the second research question. We find that each additional work-related word yields $65.27 more in monthly donations (*p<0.01*), providing evidence that donors reward operational transparency in online crowdfunding sites. We continue observing a positive effect of certification of $22.02 (*p<0.01*), an effect that is substantially smaller than the effect of a single work-related word in an update. The difference between the coefficient of Work and Certified answers our third research question and suggests that donors are more generous in rewarding campaigns that show operational transparency via work-related updates than in compensating conventional transparency via certification. The interaction between work-related updates and certification is small but significant (\$4.92; $p<0.05$), suggesting that certified charities benefit from transparency slightly more than non-certified ones.

From the control variables, we observe that campaign-level factors such as social media shares (\$10.57; $p<0.01$) and favorites (\$5.01; $p<0.05$) continue to have a positive and significant effect on donations. Finally, update-level controls show that the number of images (\$10.68; $p<0.05$) and videos (\$0.98; $p<0.05$) in the update are positively associated with donations. This finding aligns with the results of (Buell et al., 2016), who find that showing pictures as a means of transparency increases trust and in our case, donations as well.

3.5. Robustness Checks

This section checks the robustness of our results regarding model specification and potential endogeneity concerns.

3.5.1. Unique Work-Related Instances and Quadratic Effects

In our second model, we examine the effect of campaign updates containing work-related words on donations. While we control for the total number of words in the update, we also count repeated appearances of the same work-related word. Although such repeated words may indicate greater work-related content, and potentially a higher degree of transparency, it is also possible that such repetition is not informative. In the latter case, this may cause some bias in our coefficient for work-related updates. To add additional robustness to our results, we replicate our work in model (2) using a work-related variable that only includes a count of the unique instances of the words. These results are reported in

Table 3.5. We find that the coefficient for unique work-related words is moderately larger than before ($79.12 vs. $65.27 in Table 3.4) and continues to be significant (*p<0.01*).

Table 3.5 Model (2) results with unique work-related terms

	Model 2.4: FE with Unique Work-Related Words		Model 2.5: FE with Unique Work-Related Words and Quadratic Term	
Variables	Estimate	SE	Estimate	SE
Work (Unique)	79.12***	15.90	76.07***	18.20
Work (Unique)*Certified	9.07**	4.11	10.13**	4.01
Work (Unique)^2			-12.08*	6.90
Update-level Controls				
N_images_upd	11.42**	4.51	9.06***	2.93
N_videos_upd	0.86*	0.51	1.91*	0.99
Word_count_upd	3.39**	1.58	3.24***	1.20
Sent_upd	3.66	9.49	4.03	4.27
Read_upd	0.01	0.01	0.01	0.00
Fixed Effects				
Campaign Fixed Effects	Included		Included	
Time Fixed Effects	Included		Included	
Location Fixed Effects	Included		Included	
R-squared	0.58		0.59	
Time periods (months)	51		51	
Groups (campaigns)	55,477		55,477	

*refers to $p< 0.1$; ** refers to $p< 0.05$; ***refers to $p< 0.01$

We also wanted to test potential quadratic effects of the work-related variable on campaign donations. That is, we examine whether there are diminishing or increasing returns to a higher number of occurrences of work-related words in the updates of a fundraising campaign. We replicate again our work in model (2) and include a quadratic term for the count of unique work-related words. Table 3.5 also reports these results, which show that the quadratic term is negative (-$12.08) but only weakly significant (*p<0.10*). Thus, there appears to be some evidence of diminishing returns to work-related terms in the text of updates of fundraising campaigns.

3.5.2. Coarsened Exact Matching

One of the strengths of using online platforms to measure the effect of different forms of transparency is that the organizer can reach millions, instead of a few donors. With a smaller set of donors, as it would likely be the case were the study survey-based, it is possible that responses would be biased by forward-looking expectations of the campaign's results. That would occur when donors have set expectations on the transparency and likelihood of charity campaigns' success. However, the probability that thousands of donors online have set expectations for the thousands of campaigns seeking funds is much lower. This is one of the reasons for which crowdsourced data has been identified previously as less biased than datasets from smaller customer surveys (Dellarocas, 2003) or as it would in our case, potential donors.

Nevertheless, there is a possible concern of endogeneity in our models since we do not observe all the variables describing a charity or campaign, such as the intrinsic quality of the campaign or organizer. Thus, it is possible that this unobserved quality of the campaign would drive the effect of campaign updates on donations, which would render our model coefficients biased. We cannot entirely rule out omitted variable bias without the perfect randomization of updates among a randomized sample of campaigns, which is infeasible in our setting because we use secondary data. In our data the same campaign organizer creates all updates, which makes it difficult to separate the effect of the update's text with, for instance, unobserved characteristics of campaign organizers such as their reputation on the platform. However, we use advances in causal inference designed for non-experimental observational studies, such as matching methods, to reduce the bias from unobservable characteristics of the campaign (e.g., quality) (Dehejia & Wahba, 2002).

Our objective with matching is to pair campaigns that release updates with those that do not but are similar in all other observable characteristics. By matching campaigns with updates to those without updates, we ensure balance across our other covariates in the models and account for different latent variables that may explain differences across the two types of campaigns. Matched datasets have been shown to improve the estimation of causal inference (Stuart, 2010) and should help identify the effect of updates on donations more accurately.

We employ coarsened exact matching (CEM) (Iacus, King, & Porro, 2011), a recently developed matching method that has been shown to estimate causal relationships with less error than other matching techniques (Iacus, King, & Porro, 2012). The matching process has three main steps to match the treated cases (campaigns with updates) to one or more controls (campaigns without updates). First, we coarsen each matching variable by classifying each variable into strata or partitions. Second, we sort all campaigns (cases and controls) into a stratum that contain all possible interactions of the matching variables. Third, we discard the observations in the strata without at least one treated and control campaign. This results in a dataset that has an optimal balance between campaigns with updates and those without.

We begin with the 55,477 campaigns with updates and follow the progressive coarsening method outlined by Iacus, King, and Porro (2009) to coarsen the matching variables. Then, we apply the same coarsening procedure to the 52,262 campaigns without updates. The matching variables include all campaign-level observable characteristics, except for those based on the campaign’s text, such as being certified, the number of images and videos and the number of shares and favorites. Recall that we have a panel dataset (i.e., donations over time), so we match each campaign with an update in the same time period (i.e., month) to similar campaign(s) without an update.

After performing CEM, we have 35,311 campaigns with updates matched to 51,047 campaigns without updates. We employ 1:k matching since it has been shown to produce more consistent estimates (Stuart, 2010). After matching, we expect the case and control sets to have very similar characteristics (Iacus et al., 2011). This is indeed the case as shown in Table 3.6.

Table 3.6 Comparing campaigns with updates to campaigns without updates after Coarsened Exact Matching (CEM)

Variable	Treated Cases: Campaigns with Updates Mean	Control Cases: Campaigns without Updates Mean
N_images_camp	2.33	2.11
N_videos_camp	0.08	0.11
Shares_camp	38.65	31.99
Faves_camp	28.32	26.05
Groups (campaigns)	35,311	51,047

With a CEM-balanced panel dataset, we proceed to estimate the effect of campaign updates on donations over time as we did before in model (1). Table 3.7 reports the coefficient estimates. The effects of updates and certification on donations are similar in magnitude and significance as the ones reported without matching in Table 3.3. This finding provides additional robustness to our model results.

3.6. Discussion

We use an empirical approach to study crowdfunding campaigns as an additional channel humanitarian organizations can use to raise funds from private donors for emergency response. We show that being transparent matters in trust-based contexts such as online crowdfunding for emergency response. Crowdfunding campaigns that are certified and keep donors informed with updates can signal transparency to potential donors (Kornish & Hutchison-Krupat, 2017) and increase donations. However, we find that not all updates are the same. Operationally transparent updates (i.e., updates that use work-related words to describe the progress of the campaign) increase the trust of potential donors, which also reflects a rise of donations. On average, every work-related word in updates increases donations.

Table 3.7 Effect of campaign updates on crowdfunding donations for emergency relief after Coarsened Exact Matching (CEM)

	Model 1.4: OLS		Model 1.5: AR(1)		Model 1.6: FE	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	369.38*	212.02	415.05	252.75		
Updates	181.07***	50.01	176.14***	41.87	178.10***	51.09
Certified	24.19***	7.11	20.36***	6.59		
Campaign-level Controls						
N_images_camp	155.98	273.01	180.44	301.46		
N_videos_camp	45.05	59.93	65.11	64.07		
Word_count_camp	1.55***	0.61	1.77*	0.92		
Sent_camp	1.08	2.56	3.40	4.09		
Read_camp	0.01	0.01	0.01	0.01		
Shares_camp	10.01**	4.87	10.76*	6.08		
Faves_camp	2.70***	1.01	2.69**	1.05		
Fixed Effects						
Campaign Fixed Effects					Included	
Time Fixed Effects	Included		Included		Included	
Location Fixed Effects	Included		Included		Included	
R-squared	0.61		0.63		0.69	
Time periods (months)	44		44		44	
Groups (campaigns)	86,358		86,358		86,358	

*refers to $p< 0.1$; **refers to $p< 0.05$; ***refers to $p< 0.01$

In the crowdfunding setting under study, the organizer can also show transparency to potential donors by adding the tag “certified” to the campaign. The “certified” tag assures donors that the campaign benefits a charity nonprofit with 501(c)(3) status. To get this status, the organizer has to disclose legal and financial information fully to the government. In line with previous studies, our results show that conventional transparency via certification give economic benefits to the organization (Kraft et al., 2017; Podolny, 1993; Rao, 1994).

Interestingly, we find that the positive effects of operational transparency go beyond the benefits of conventional transparency. Certified charities, which report their operations to the government, show a rise in donations below the increase we find for operational transparent updates, which communicate work to potential donors. These effects can be contingent to the context under study (emergency relief campaigns). Donors funding emergency campaigns may care more about receiving constant updates about the current work in the field than about the certification of the organization.

Our contribution to the humanitarian funding literature is twofold. First, we consider crowdfunding platforms as a new channel to raise funds for emergency relief, which can also serve as a means to increase transparency in humanitarian operations. Second, we add to established literature which states that private donors do not care about the efficiency of emergency operations (Eftekhar et al., 2017; Hyndman & McDonnell, 2009). We contribute to this literature by showing that private donors pay attention to transparency and the work performed during emergency relief operations when making donation decisions. We explain this contribution with the increased transparency that crowdfunding platforms offer. In typical donations settings, in which private donors give money to organizations, they cannot track the specific work performed with their donations. Instead, crowdfunding platforms allow private donors to follow the work and evaluate the transparency of organizations.

There are several limitations in our analysis associated with the data obtained from the crowdfunding platform. First, the number of social media likes and shares are time-varying variables, but it is only observed at the aggregate level for the time the data was collected. That is, there are no time stamps associated to each share or fave. This makes it upwardly biased for older campaigns, which have had more time to collect likes or shares. To add robustness, we divide the measure by the age of the campaign as standardization and observe consistent results. Second, the specificity of the donations data is somewhat limited. Within the first 30 days of data collection, we observe donations at the campaign-day level. Unfortunately, the rest of the data has month-level specificity, which is why we employ models at the campaign-month level. Third, we are not able to separate the effect of certification and work-related updates between new and recurrent donors. However, we believe that the behavior of recurrent donors does not drive our findings because of the nature of online crowdfunding platforms. As the goal of these platforms is to raise small amounts from a large pool of donors, the impact of recurrent donors is limited.

This work has managerial implications both for humanitarian organizations willing to start online crowdfunding campaigns to collect funds from private donors and for crowdfunding platforms. First, as we find that updates have a positive effect on donations, campaign organizers can increase funding by keeping their donors informed on a regular basis about the progress of the campaign. However, our results show that the type of update matters because operational transparency increases benefits to the campaign. Hence, campaign organizers can focus their efforts on publishing operationally transparent updates; that is, updates that include work-related words to describe what the campaign has been doing with the collected funds. Second, crowdfunding platforms can also build on these insights to guide campaign organizers on how to be more transparent in order to access more funding. In fact, a large crowdfunding platform supporting start-ups has already started motivating campaign organizers to post regular updates in campaigns. This platform implicitly suggests that these updates should be operationally transparent by asking the organizers to be honest and open on how the funds are spent and to describe the successes and milestones achieved.

Our work also has implications for future research. First, the higher positive effect of operational transparency over conventional transparency may be context dependent. Future work can explore if conventional transparency has a different effect compared to operational transparency in slow-onset settings such as development programs. Second, researchers can consider website design decisions. In the crowdfunding platform under study, designers seem to give an increased emphasis (i.e., larger website space) to updates compared to the emphasis given to the certification process. When a campaign is certified, it appears as a relatively small tag in the campaign website. Therefore, future work can consider the impact of these kinds of design decisions on donations. Third, our empirical analysis only uses secondary data. Even if we try to control for the heterogeneity of campaigns and updates using fixed effects and coarsened exact matching, there are still limitations to the correct identification of the causal mechanisms. Future research could include experimental designs to investigate how much our current results are robust to other causal mechanisms such as the quality and type of images and videos included in the campaigns.

Chapter 4. Volunteer Management in Charity Storehouses: Volunteer Experience, Congestion and Operational Performance[4]

Abstract: We study volunteer management at a large faith-based organization that operates a charity storehouse. The whole supply chain works exclusively with volunteers from supply to delivery. We model the preparation of beneficiaries' orders by volunteers in the storehouse as a function of volunteer experience and congestion. We explore how operational decisions, such as the type of volunteers' pairing in teams and whether to allow or impede congestion, affect two performance measures: on-time order preparation rate and additional time to prepare the orders. Using empirical data, we build a simulation model to study these relations. Results show that when both demand of orders and supply of volunteers are predictable, the strategy of pairing volunteers with different experience levels (mixed-pairing) outperforms the strategy of pairing volunteers with similar experience levels (no-mixed pairing). However, under disaster conditions that combine a high supply of volunteers with congestion at the storehouse, mixed-pairing performs worse than no-mixed pairing. Moreover, impeding congestion is adequate when the supply of volunteers increases above the needs of the storehouse. However, when the demand of orders rises simultaneously with the supply of volunteers, impeding congestion does not work well. In these cases, a policy that allows for some congestion at the storehouse performs better.

Keywords: supply chain management, volunteer management, agent-based modeling, humanitarian logistics

[4] Paper co-authored with Alfonso Pedraza-Martinez and Maria Besiou

4.1. Introduction

More than 62 million volunteers donated over 7.9 billion hours of service to charitable organizations in the United States in 2015. These donations are valued at approximately 184 billion USD (Independent-Sector, 2016). While the contributions of volunteers are critical to nonprofit organizations, and in particular to humanitarian organizations to operate their supply chains, managing volunteers is challenging for such organizations due to the high uncertainty inherent to volunteering. Humanitarian organizations face high variability both in volunteer experience and in volunteer arrivals. The heterogeneity of volunteer experience makes it difficult for humanitarian organizations to plan the allocation of volunteers to tasks because inexperienced volunteers can delay supply chain operations and do more harm than good in their attempts to help (Jenkin, 2015). Moreover, uncertain volunteer arrival patterns can result in congestion, particularly when large numbers of volunteers arrive to a particular zone in the aftermath of a disaster. We study the combined effect of volunteer experience and congestion on the operational performance of a charity storehouse that delivers food and hygiene items to people in need.

The storehouse we study belongs to a large faith-based organization based in the United States. The storehouse is a steady aid delivery system characterized by unlimited supply, as it is located next to a large warehouse that belongs to the same organization and the warehouse can replenish the storehouse immediately if required. Moreover, weekly demand is highly predictable, as it is composed of beneficiaries affiliated with the organization and is known one week in advance of order preparation. Thus, the main uncertainty in this operation comes from the experience and arrivals of volunteers that donate time to prepare the weekly orders for the beneficiaries. This unique setting allows us to focus on the effect of volunteering on the operational performance of the supply chain. Once we model the steady system, we introduce disaster features via experimental treatments. First, we vary the supply of volunteers. Next, we change the demand of orders (Besiou et al., 2014). Both supply of volunteers and demand increase uncontrollably during disaster response (Fritz & Mathewson, 1957).

We operationalize volunteer experience, storehouse congestion and operational performance as follows. First, we consider two types of volunteers arriving in the storehouse: experienced (Exp) and inexperienced (Inexp), who can work in mixed (Exp-Inexp) or no-mixed (Exp-Exp, Inexp-Inexp) teams. Second, we study two congestion policies: allowing congestion or impeding congestion. We allow congestion by letting all the arriving volunteers enter the storehouse and impede congestion by limiting the number of volunteers to the maximum capacity of the storehouse. The choice of congestion policy is not a trivial decision. If congestion is allowed, when the number of volunteers exceeds the capacity of the storehouse, processes slow down and completing the orders takes longer. If congestion is limited to the capacity of the storehouse, volunteers that are not allowed to help leave the storehouse and reduce the capacity of the organization to complete all orders. Third, we analyze two operational performance measures at the storehouse level: (i) On-time order preparation rate, which refers to the proportion of orders that are completed after five hours of operation in the storehouse, the expected amount of time to prepare all orders and start delivery and (ii) the additional time to prepare the remaining orders, which refers to the delay to finish order preparation. To understand the relationships among these variables, we collect empirical data and develop a simulation study.

We collect data on the organization and the storehouse processes via participant observation, interviews and archival data. We use participant observation and interviews to study the order preparation process in the storehouse and how volunteer experience and congestion affect the duration of order preparation. We use archival data for over three years to characterize the distribution of the weekly demand (orders) and volunteer arrivals in the storehouse. Using this data, we build an agent-based simulation (ABS) model to explore the drivers of the two operational performance measures (on-time order preparation rate and additional time to complete the orders) at the storehouse level, and we design eight (4x2) experimental treatments varying volunteer experience (only Exp, only Inexp, mixed pairing, no-mixed pairing) and congestion in the storehouse (with and without congestion). We use ABS because we can represent reality without interfering with volunteers' work. This is especially important during disaster response operations when data collection poses logistics challenges. Using the ABS model, we first study the scenario under steady conditions in which the demand of the beneficiaries is known in advance and cannot be lost since the volunteers will stay in the storehouse as long as needed to prepare all the orders. We run sensitivity analysis to test the robustness of the results to changes in the ratio of Exp and Inexp volunteers, to the types of learning curves and to the initial experience level of the Inexp volunteers. Then, we put the model through three different disaster conditions: (1) high demand, (2) high supply of volunteers and (3) high demand and high supply. We explore again the drivers of both performance measures at the storehouse level in order to understand the best policies to manage volunteer experience and congestion under these extreme scenarios.

Results show that under steady conditions, when both experienced and inexperienced volunteers arrive, a mixed-pairing strategy is better than no-mixed pairing because it facilitates collaboration and learning from one another. In addition, a policy that limits or allows congestion does not drive differences in the performance measures. However, under disaster conditions the results for the pairing strategy and the congestion policy have different performance outcomes. For the pairing strategy, we find that combining a high supply of volunteers with congestion in the storehouse, a mixed-pairing strategy that facilitates collaboration performs worse than a no-mixed pairing strategy. The no-mixed pairing strategy has higher performance for two reasons. First, based on our analysis, the high supply condition increases the availability of experienced volunteers in the storehouse. Second, as experienced teams do not have to learn, the speed of their order preparation suffers less from the congestion in the storehouse. Therefore, letting the teams Exp-Exp work on their own is more efficient than combining them with inexperienced volunteers.

For the congestion policy, results show that when the supply of volunteers increases above the needs of the system, a policy that impedes congestion delivers the best performance for the supply chain; however, the number of orders limits the effectiveness of this policy. When the demand rises simultaneously with the supply of volunteers, impeding congestion does not work well. When congestion is restricted, some of the volunteers that are not allowed to enter the storehouse do not wait for the opportunity to help and leave the system. As they leave, the number of volunteers available to complete the orders reduces, impairing the ability of the organization to satisfy the demand. In these situations, an intermediate policy that allows for some congestion in the storehouse works better than an extreme policy which completely allows or impedes congestion. Allowing for some congestion lessens the negative impacts of an extreme policy: it increases the speed of the fully congested storehouse and reduces the number of volunteers that are forced to leave the system.

Our findings contribute to the literature on supply chain management by showing boundary conditions for the effectiveness of policies that (i) allow collaboration between experienced and inexperienced volunteers and (ii) limit (but do not eliminate) congestion. To our knowledge, there are no operations management studies examining the effects of volunteer experience and congestion on the operational performance of humanitarian organizations.

4.2. Background: Volunteer Management, Experience and Congestion

Previous operational research on volunteer management has addressed two main topics: volunteer satisfaction and volunteer scheduling. Volunteer satisfaction has received attention because when volunteers are satisfied, they contribute more of their time and money to the organization and ask family and friends to volunteer as well (Wisner et al., 2005). Researchers have found a number of enhancers of volunteer satisfaction: working conditions, social relations and perception of the task. First, volunteers are satisfied when working conditions include schedule flexibility, orientation and training, empowerment, rewards, recognition and even economic incentives (Lacetera et al., 2014; Wisner et al., 2005). Second, volunteers usually have a relational motive to join volunteer assignments, therefore, creating opportunities to make social connections and friends during the execution of the task may satisfy current volunteers and increase volunteerism (Prouteau & Wolff, 2008; Willems & Walk, 2013). Third, volunteers appreciate the opportunity to be assigned to tasks that are considered meaningful and to which they feel they can contribute; when volunteers feel they are underutilized, they tend to donate less of their time in the future (Sampson, 2006).

Regarding volunteer scheduling, researchers have compared how volunteer labor assignment differs from traditional labor assignment, considering cost structures, objective functions and constraints (Sampson, 2006). They have developed multi-criteria optimization models to minimize volunteer labor shortages and scheduling costs while maximizing the satisfaction of volunteers' preferences (Falasca & Zobel, 2012; Falasca et al., 2011). Others have considered stochastic rates of volunteer arrival and abandonment by using analytical queuing systems to model optimal assignment policies for spontaneous volunteers to different activities (Lodree & Davis, 2016; Mayorga, Lodree, & Wolczynski, 2017). However, even if some of this research acknowledges the uncertainty in volunteer skills and experience level (Mayorga et al., 2017; Wisner et al., 2005), most of these studies assume that the volunteers have the required skills and experience to perform their labor assignments.

4.2.1. Volunteer Management and Experience

Some scholars have started to incorporate the variable of people's experience in workforce planning, including staffing and scheduling decisions (De Bruecker, Van Den Bergh, Beliën, & Demeulemeester, 2015), but only few studies in volunteer management have done so. Research on volunteer ability focuses on disaster settings when the needs of the population, the availability of volunteers and their experience change over time. Lassiter et al. (2014, 2015) develop multi-criteria optimization models to minimize unmet task demand and maximize volunteer assignment preferences while accounting for the experience of volunteers, the experience required in the volunteering task, volunteer training opportunities and volunteer attrition. They find that optimal strategies for organizations include training inexperienced volunteers at the very beginning of the disasters and matching volunteer preferences only up to a certain threshold.

The experience of workers can be improved with training; however, they can also learn and increase experience during the task assignment through interaction with more experienced workers. When employees work together, they can collaborate and share knowledge, improving organizational performance (J. Y. Lee, Swink, & Pandejpong, 2011; Siemsen, Balasubramanian, & Roth, 2007). Collaboration is higher when employees work on interdependent (instead of independent) tasks (Siemsen et al., 2007). We advance the study of the heterogeneity in volunteer experience and their learning process by building on the previous positive findings of collaboration for workers. In particular, we investigate how humanitarian organizations should manage experienced and inexperienced volunteers in order to have a positive effect on the operational performance of the supply chain. We study whether the learning derived from collaboration between experienced and inexperienced volunteers is always more effective in achieving the best performance.

4.2.2. Volunteer Management and Congestion

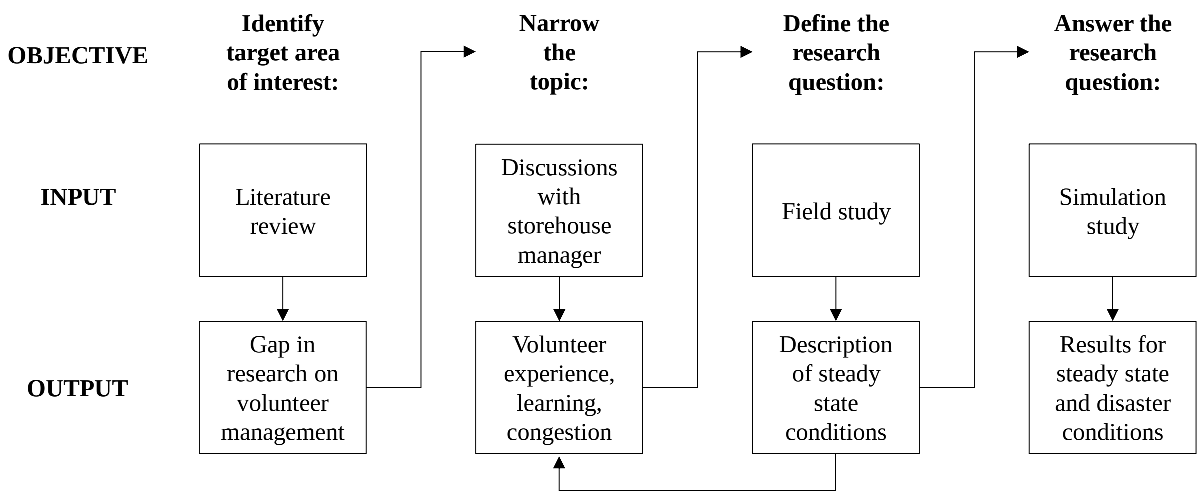
Congestion in volunteer management is related to convergence (Fritz & Mathewson, 1957). The literature on convergence studies the types of people gathering after a disaster (Fritz & Mathewson, 1957; Kendra & Wachtendorf, 2001), the distribution of arrivals and duration of the convergence period (Lodree & Davis, 2016) and the advantages and disadvantages of convergence (Barraket et al., 2013; Tierney, 2003; Wachtendorf & Kendra, 2004; Whittaker, McLennan, & Handmer, 2015). The main benefit of convergence is increasing the capacity of organizations to respond to peaks in demand, but when the number of people convening is large, convergence also creates congestion. Congestion can obstruct coordination and deviate the allocation of experienced resources to focus on crowd control or training. It can also slow down the processes and the response itself.

To our knowledge, the effects of volunteer congestion on operational performance measures of the supply chain have not been evaluated. We study how to manage congestion in a storehouse by considering two different congestion policies and evaluating their impact on operational measures. The first policy allows for congestion in the storehouse, accepting all the volunteers that arrive to help, while the second policy completely limits congestion, receiving volunteers in the storehouse only up to its capacity. We study which congestion policy works better under different steady and disaster conditions.

4.3. Research Design

Our research follows the multi-method approach suggested by Besiou & Van Wassenhove (2015), who discuss that in the case of socially responsible problems, as ours, researchers need to use a combination of different methods: literature review to make links with current research and identify remaining gaps, case study to collect qualitative and quantitative data and simulation to get a holistic understanding of the system's behavior. After building the simulation model, we follow Besiou et al. (2014) to test the model by replicating the collected data and validate it with different sensitivity analyses. Finally, using the simulation model, we put the system under extreme conditions to mimic disaster scenarios and revise the behavior of the storehouse under different policies. Figure 4.1 summarizes the research design.

Figure 4.1 Research process (based on Pedraza-Martinez et al. (2011)).



4.3.1. Field Study

The data collection took place from June to December 2014 during which the authors visited the storehouse site seven times. We collected demand data both on usual days and before Thanksgiving, when the demand peaks. We gathered data via participant observation, interviews and archival data. We used overt participant observation to study volunteers' learning curve and the processing time of the orders, interviews to understand the process and the criteria for volunteer pairing and archival data to capture the historical patterns for both order demand and volunteer arrivals.

We conducted semi-structured interviews with senior volunteers. As suggested in the literature (Luker, 1984), we sent transcriptions to the interviewees to check for accuracy and no one objected it. In addition to the in-depth interviews with the senior volunteers, we also had informal discussions with less experienced volunteers, who were promised confidentiality and anonymity. During observations, we wrote down important pieces of dialogue. After each visit, we expanded these records into detailed field notes, leading to extensive summaries on our visits. Hence, the project's written records contain literature, notes from the organization and archival materials. Examining these documents enabled us to crosscheck some of the assertions made in interviews with documentary evidence (as we did, for example, regarding the number of volunteers on Tuesday mornings). To avoid potential bias, we did not share results with the senior volunteers during the data collection (Calarco, 2011); we did that only at the end of the project.

Table 4.1 presents the dates, time spent and tasks performed during each visit. During the data collection, we were primarily observers and assisted only when that facilitated the data collection process, for example, in order to understand the volunteers' learning curve better. Table 4.2 summarizes the categories of data and relevant parameters collected during the visits. We have archival data for the demand (i.e. weekly orders) from 2011 to 2014 and volunteers' walk-ins to the storehouse from 2012 to 2014. The demand follows a lognormal distribution with mean 69.33 weekly orders (standard deviation 11.27) while the average number of weekly volunteer arrivals is 30.66 (standard deviation 9.74).

Table 4.1 Dates, time spent and tasks performed during each visit

Date	Time (hrs)	Tasks performed
Wed 4/6/2014	1.5	Interview with storehouse manager
Tue 10/6/2014	5	Understand how orders are prepared at storehouse, build trust through volunteering
Tue 1/7/2014	9	Understand truck delivery, build trust through volunteering
Wed 3/9/2014	1.5	Feedback from storehouse manager on first conceptual model
Wed 5/11/2014	1.5	Understand operations of pick-up at storehouse, build trust through volunteering
Tue 18/11/2014	5	Collect data on the orders preparation through observation (1 week before Thanksgiving, double orders than usual to handle)
Wed 17/12/2014	1.5	Discuss preliminary findings

From our field observations, we get more detail about the characteristics and behavior of the volunteers and the supply chain. We observe that the usual ratio between experienced and inexperienced volunteers is 1:2, i.e. there is one experienced volunteer for two inexperienced ones. The order preparation process is planned to take around five hours, but volunteers do not usually stay all this time. Instead, volunteers arrive at different times and stay for different lengths. We observe that roughly 50% of the volunteers arrive in the first hour, 10% arrive during the second hour, 30% in the third hour and the last 10% in the fourth hour. Usually, there are no arrivals during the fifth hour.

During the order processing, we observe that the amount of time to prepare each order varies with the experience of the volunteers and the congestion of the storehouse. For a pair of experienced volunteers in an uncongested storehouse, preparing an order takes around 28 minutes. If volunteers are inexperienced or the storehouse is congested, this time increases. Finally, in the process of leaving, inexperienced volunteers are more likely to exit the storehouse than experienced volunteers are. Experienced volunteers usually stay for longer periods or until all the orders are prepared. In general, volunteers prepare between 1 and 7 orders before leaving the system.

Table 4.2 Data categories and relevant parameters collected during field visits

Data category	Description	Relevant parameters
Demand	Historical secondary data on weekly orders from 2011 to 2014	Lognormal distribution with mean 69.33 weekly orders and standard deviation 11.27
Volunteer arrivals	Historical secondary data on weekly volunteer arrivals from 2012 to 2014	Average weekly arrivals: 30.66 volunteers (standard deviation 9.74)
Volunteer experience	Primary data on the experience of each volunteer and the mix of experienced and inexperienced volunteers in a day of work	Ratio between experienced and inexperienced volunteers is 1:2
Order preparation	Primary data on the average time spent in an order by a pair of volunteers	Average preparation time by a team of experienced volunteers: 28 min
Duration of stay	Primary data on the number of orders prepared before a volunteer leaves the system	Between 1 and 7 orders prepared before a volunteer leaves the system

4.3.2. Setting

We study a faith-based organization that relies heavily on volunteers to run their daily operations, both during steady and disaster conditions. Therefore, it provides a suitable setting to study volunteer management and its impact on the operational performance of the supply chain. The organization usually has an unlimited supply of goods and volunteers because it owns land (and produce) and because of generous monetary and time donations from its members. The main challenge that the organization currently faces is volunteer management. Volunteers operate in a small storehouse, and due to the nature of their labor, they need to work in groups of two. Hence, it is challenging for the organization to select the right teams for the job, and it is hard to decide whether to allow or avoid congestion in the storehouse.

Given the data collection challenges during disaster situations (Pedraza-Martinez & Van Wassenhove, 2016; Starr & Van Wassenhove, 2014), we gathered data on the organization's supply chain during steady conditions in which the storehouse works well. Our aim is to model these steady conditions and explore the drivers of two operational performance measures: on-time order preparation and additional time to prepare the orders. Then, we put the model through extreme conditions to simulate disaster scenarios and review again the drivers of both performance measures at the storehouse level in order to understand the best strategies to manage volunteers and congestion under these scenarios.

4.3.2.1. The organization

The organization, which we keep confidential, is in the top five of the largest churches in membership in the US and is one of the largest landowners besides the US government. The organization has two central warehouses in the Midwest region of the US: Indianapolis and Atlanta. The Indianapolis warehouse serves 11 storehouses, including the one under study. The storehouse we study covers approximately 60 congregations and 20 branches in the states of Indiana and Kentucky. Each congregation has between 400 and 600 members and a Bishop as a leader. In addition to the national programs, the organization operates all over the world doing disaster response. For instance, in response to the Asian Tsunami, they sent body bags and later built schools with computers and sent books. In the case of Haiti, they donated a mobile hospital. Depending on the disaster, the organization also sends volunteers to help; for example, after Hurricane Hugo in Florida in 1989 out of the 9000 volunteers that were helping in the area, 5000 were members of the organization.

Organization's members are the main donors of both time and money. As a volunteer said, "*You help so many people; it is a good program. When people are helping other people, they are happy. Helping people is the most important thing*." Moreover, members are also encouraged to donate money. The organization teaches the concept of tithing, in which members are encouraged to return 10% of their earnings back to the organization. Additionally, the first Sunday of the month, members fast and contribute what they save in food to help purchase food for the storehouse.

4.3.2.2. Demand and Supply

The storehouse provides commodities such as vegetables, meat and dairy products to people in need (henceforth referred to as beneficiaries). The beneficiaries are usually members of the organization and their families, who have lost their jobs or are old or sick. On Sunday, the beneficiary meets the president of the organization, and they plan a two-week menu day by day. The president of the organization maps the menu into an order of commodities. For example, on Monday the family has cereal for breakfast, hamburgers for lunch, and fruit and cheese for dinner. This translates into cereal, milk, bread, meat, tomato, onion, etc. The Bishop signs the order to authorize it, and the order is sent to the storehouse by mail, email, in person, etc. Orders become anonymous to avoid any stigma. The orders that the storehouse receives by Sunday at midnight are prepared during the coming week with the help of volunteers. Orders are prepared weekly; however, beneficiaries can only order every two weeks. Demand may vary between 20 to 60 orders per day per route served. The storehouse serves five fixed routes that cover 18 communities. Thanksgiving and Christmas usually mark peak demand. The organization does not register how many people they help; instead, they register the number of orders delivered.

The standard operation of the supply chain holds inventory for three months. The inventory of cans and non-perishable items is ordered once per month and may last up to six months. Fresh products, such as fruit, vegetables, bread and meat, are ordered weekly. The meat products include chicken, turkey and roasted pork. The organization’s farm branches supply approximately 80% of the commodities delivered by the storehouse.

4.3.2.3. Volunteers

The organization appoints a senior volunteer and his wife as storehouse managers every 18 months; they also serve as volunteers. The storehouse manager does not want the orders to be spoiled due to the lack of labor to handle them. Therefore, the manager plans volunteer supply on a yearly basis. Based on demand records from the previous year and the number of volunteering congregations, the storehouse manager assigns congregations to different weeks. The manager communicates the plan to the Bishop of each congregation, and the Bishop asks for volunteers from the members of the congregation. Based on the schedule, the members of a particular congregation go to the storehouse and donate their time. This is the largest source of volunteers. Volunteers range from those that have been volunteering at the storehouse for more than fifteen years to those that go once in a lifetime. Experienced volunteers go directly to the storehouse, independently from the congregation. Beneficiary volunteering depends mostly on proximity to the storehouse, increasing uncertainty in arrivals.

4.3.2.4. Order Preparation Process

On Tuesday, for around five hours, a group of volunteers prepares the orders for the week. After orders are prepared, they are delivered to beneficiaries with a truck. Less than 1% of the orders are lost due to truck delays or bad communication with the beneficiaries. In that case, the order will return to the storehouse, and either someone from the Bishop's office will drive it to the beneficiaries another day or the local Bishop of the beneficiaries' congregation will go with the family to the supermarket to buy whatever they need and pay for that. The volunteers go through the following processes in the storehouse when preparing the orders for the week.

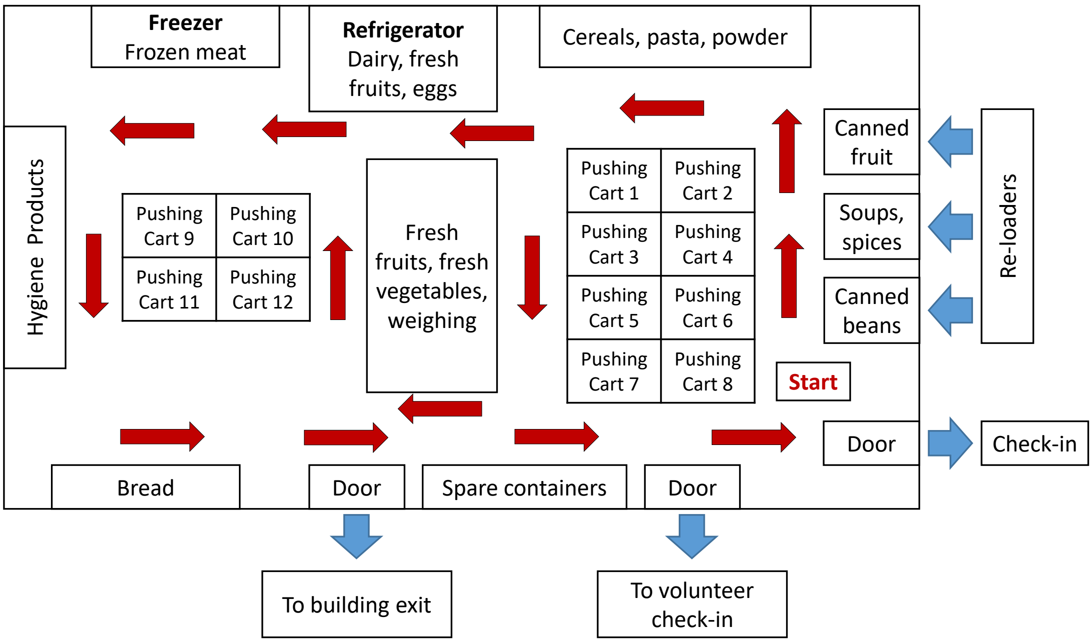
Volunteers arrive. There are usually about 30 volunteers that come on Tuesdays to consolidate the orders for delivery by truck. Some volunteers arrive to the storehouse before work (from 6:00 am to 8:00 am), while others arrive after 8:00 am for the later shift. Some volunteers may be late, which results in the volunteers staying later, or less often, they may not show up.

Volunteers find a potential partner. The storehouse manager pairs volunteers based on experience so that experienced volunteers coach the new ones, aiming to accelerate the learning process. When several volunteers arrive together, they form their own teams. The combination of skills seem to play a role on order preparation: Exp-Exp is the fastest; Inexp-Inexp is the slowest. However, it is unclear whether allowing mixed teams improves the system's operational performance more than in the case when only no-mixed ones are formed.

Volunteers form a team. Most volunteers work on the "other items" line (depicted in Figure 4.2), where they form teams of two people to pick products such as canned beans, cereals, dairy products, fresh fruits, meat and bread for each order. When a pair of volunteers forms (henceforth referred to as a team), they first sign the attendance sheet and receive an order form at the volunteer check-in area. In the "other items" line, up to twelve teams can work at the same time with no congestion. When more than 12 teams coincide at the same time, the storehouse experiences congestion, and the process slows down.

Volunteers receive an incomplete order. Each team picks the items of one order at a time. The preparation time of each order (i.e. service rate) depends on the experience of the volunteers and the congestion in the line. The sequence of the items in the order sheet follows the same order of the products in the picking line (Figure 4.2). For instance, the order lists canned beans, soups and canned fruit first, while it lists hygiene products and bread last. This structure makes it easier for those without experience to find the commodities to fill the order.

Figure 4.2 "Other items" line



Volunteers prepare the order. The team collects a "pushing" cart that has two plastic containers and a little bag with post-its, a red pen and a black marker. The post-its are used to mark the name of the order and stick it into the containers. The red pen is used to write the number of units of product collected next to the number of units required in the order form. Each team puts three paper bags in each plastic container. The marker is used to mark the paper bags with the name of the order. After leaving the check-in area, one of the team members takes a small paper box and begins picking the items while the second member checks. Once an order is filled, the team pushes the cart out of the line to the pallet area. The pallet supervisor checks that all the items in the order have been picked correctly. Another team puts the boxes in a pallet. Pallets are taken either to a refrigerator (if the order will be delivered the same day) or to a freezer if the order will be delivered later that week.

Volunteers get experience. If the volunteers are experienced, an average-sized order will typically take around 28 minutes. If there is a team of inexperienced volunteers, then it will take five minutes more on average. However, inexperienced volunteers learn both from the interaction with experienced volunteers and from the process of completing the orders.

4.3.3. Agent-Based Simulation Model

We use the primary and secondary information about the organization's supply chain processes and volunteer arrivals to build an agent-based simulation (ABS) model. We use ABS to understand the drivers of on-time order preparation at the storehouse level, in particular the effects of volunteer experience and congestion, for three main reasons. First, as other simulation techniques, ABS allows us to represent the reality of volunteer management without actually interfering with their job. We start with a scenario under steady conditions, which we model considering both archival data and field observations (Table 4.2), but we then incorporate extreme conditions to simulate a disaster for which data is difficult to collect in real life. Moreover, ABS allows us to run different simulation scenarios to study the effects of different factors on order preparation systematically, both individually and in combination.

Second, we choose ABS instead of other simulation techniques, such as system dynamics and discrete-event simulation, due to the level of detail and evolution of the agents over time that our analysis requires. System dynamics is a useful technique to simulate scenarios with a high level of abstraction using aggregate constructs (Borshchev & Filippov, 2004), but our aim is to model the individual behavior of the volunteers instead of aggregating them as a construct in the system. On the other hand, discrete-event simulation is useful to focus on entities; however, these entities are considered passive objects usually (Borshchev & Filippov, 2004) and our goal is to model the volunteers as active agents able to learn over time. ABS allowed us to have both: the detailed focus on volunteers as our active unit of analysis, able to learn by following specified behavioral rules.

Third, most volunteer models do not account for heterogeneity in the experience or skills of the volunteers (for an exception, see Lassiter et al. (2014, 2015)). Instead, we are interested in studying the setting in which agents are heterogeneous in their experience and their behavior can lead to congestion in the storehouse, which is rather typical during disaster response. ABS not only allows us to account for this heterogeneity, but also to model the higher-level behavior of the system that emerges due to individual-level interactions, providing a bottom-up approach (Altay & Pal, 2014; Xiang, Kennedy, & Madey, 2005). Furthermore, ABS lets us observe how the emerged system behavior influences the interactions of the agents in turn.

We describe the model in detail below, following the ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2006, 2010). Overview comprises the purpose, entities, state variables and scales, and process overview and scheduling. Design concepts refer to conceptual frameworks considered in the model. Details include initialization, data input and submodels.

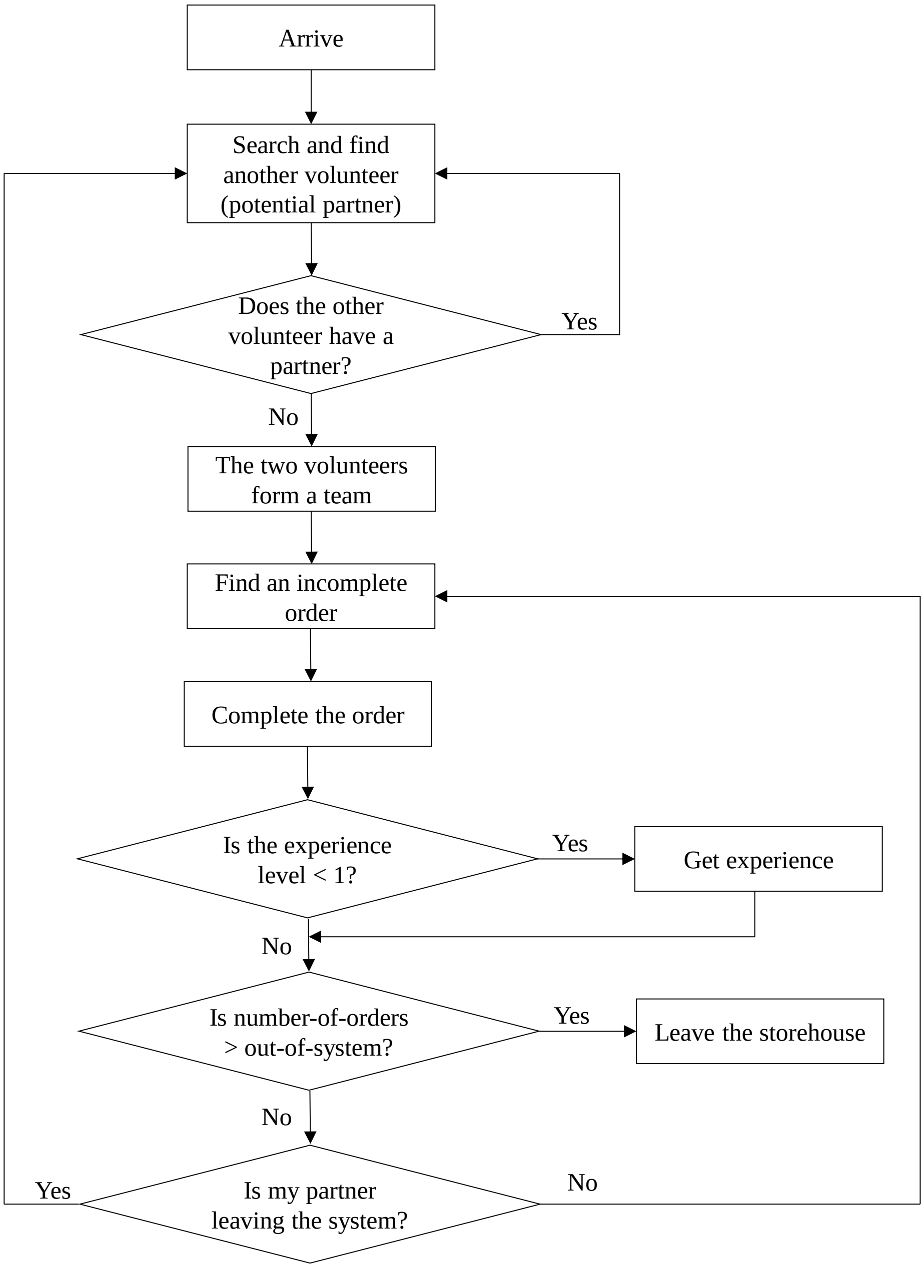
Purpose. The ABS focuses on the order preparation process that volunteers perform on Tuesdays in the storehouse. The purpose of the model is to understand how volunteer experience in combination with congestion affect the on-time order preparation of a supply chain that relies heavily on volunteers. We do this by capturing the dynamics and behavior of the volunteers as they interact with each other and with the system.

Entities, state variables and scales. The model comprises two main entities: volunteers and orders. Volunteers are characterized by the state variables: identity number, experience level, partner, number-of-orders and out-of-the-system. The experience level changes according to the type of volunteer. Experience level is a fraction between 0.5 and 1.

Experienced volunteers arrive in the system with an experience level of 1, while inexperienced volunteers arrive with an experience level of 0.5. We use 0.5 to consider that the structure of the storehouse under study (Figure 4.2) allows volunteers to familiarize with the order preparation process easily. However, volunteers can learn and get experience from completing orders, and therefore, their experience level may increase up to 1 over time. Partner is a binary variable that indicates whether the volunteer is alone or already coupled with another one as part of a team. The number-of-orders variable accumulates the amount of orders that the volunteer has completed. The out-of-the-system variable is a randomly generated number (between 1 and 7) that indicates the number of orders that the volunteer will complete before leaving the storehouse. Orders are characterized by the state variables: identity number and processing time. At the beginning, all orders require the same processing time (28 minutes).

Process overview and scheduling. One time step represents one minute, and each run simulates the volunteering work of preparing orders in the storehouse on a Tuesday. Each time step runs different processes for the volunteers in the following order: arrive, find a potential partner, form teams, find an incomplete order, complete order, get experience and leave the storehouse. Figure 4.3 shows these processes together with the decision rules made by the volunteers. In the simulation model, other processes occur separately to the ones executed by the volunteers. For instance, the orders recalculate the time required for their preparation, and supply chain performance indicators such as on-time order preparation and additional time to prepare the orders are computed.

Figure 4.3 Processes and decision rules of volunteers in the ABS



Design concepts. Basic principles behind the model design include convergence, learning and congestion. From the literature, we know that the number of volunteers increases according to the need, an effect that is called convergence (Barraket et al., 2013; Kendra & Wachtendorf, 2001; Tierney, 2003; Wachtendorf & Kendra, 2004). Therefore, we also link the number of volunteers arriving to the storehouse according to the demand and keep it close to the archival data. Second, we build on the literature of learning (J. Y. Lee et al., 2011; Siemsen et al., 2007) to model the way in which volunteers learn from their partners and acquire experience over time. Third, we acknowledge that the storehouse has a limited capacity to behave efficiently. Therefore, when this capacity is exceeded, we account for congestion by imposing longer processing times (estimated with real data) to complete the orders in order to reflect that volunteers will move more slowly in the storehouse. These design concepts also help us transition to the disaster response scenario.

The emergent behavior of the system is a result of both the characteristics of the individual volunteers (i.e. experience level) and operational decisions of the storehouse manager. In particular, the storehouse manager can decide on how to pair the volunteers to work together and if congestion will be allowed in the storehouse. In practice, this is not an easy decision for the storehouse manager. On the one hand, allowing for congestion in the storehouse despite the reduction in speed is attractive because sending people away may demotivate current and future volunteers. On the other hand, congestion can also have negative behavioral aspects: volunteers might not like it and, therefore, may leave the storehouse earlier or may not come back.

In the model, volunteers are assumed to know their own and their partner's level of experience, so that they can correctly pair to form a team. They also know whether an order is still open or is already completed, but they do not know in advance how long the order is going to take. Volunteers interact directly both among themselves and with orders. Interactions among volunteers occur when they form a pair and start working together as a team. Interactions with orders happen when the team works on an open order for a certain time until they prepare it. Indirect interactions between volunteers may occur due to congestion.

Initialization. At the beginning of the simulation, all the orders arrive, but only 50% of the volunteers do. The demand (i.e. number of orders) is generated randomly following the empirical lognormal distribution. Orders start with the same required processing time (28 minutes), but this value may increase during the simulation according to the level of volunteer experience and congestion. The total number of volunteers planned to arrive is computed as 45% of the demand. Each volunteer starts with zero orders completed and with no partner.

At the time of initialization, three main parameters of the model can change. First, the model can allow changes in the type of the volunteers arriving in the storehouse: only experienced volunteers (Exp), only inexperienced volunteers (Inexp) or mixed volunteers. Second, if a mixed type of volunteers arrives to the system, the model selects how volunteers will pair to form the team. The pairing can be done following two types of strategies: mixed pairing (Exp-Inexp) or no-mixed pairing (Exp-Exp, Inexp-Inexp).This choice of pairing reflects the reality of volunteer management in the storehouse. Volunteers on their own may prefer the no-mixed pairing since the experienced volunteers may know each other in advance, while the storehouse manager may push for mixed pairing to improve the learning process and volunteer experience. Third, it is possible to allow or impede congestion in the storehouse. When congestion is allowed, the storehouse can have over 12 teams of volunteers working at the same time, but at a reduced speed. When congestion is not allowed, only new pairs of volunteers are formed if the total number of teams in the storehouse is smaller than 12. As this is a stochastic process, sometimes more than 12 teams are formed at the same time. In these situations, the model computes the excess and chooses newly formed teams of volunteers randomly to eliminate them from the system.

Model Validation. We design the model with input from both archival data and field observations (Table 4.2). Table 4.3 shows how the archival (real) data compares to the simulated data that is being generated by the agent-based model.

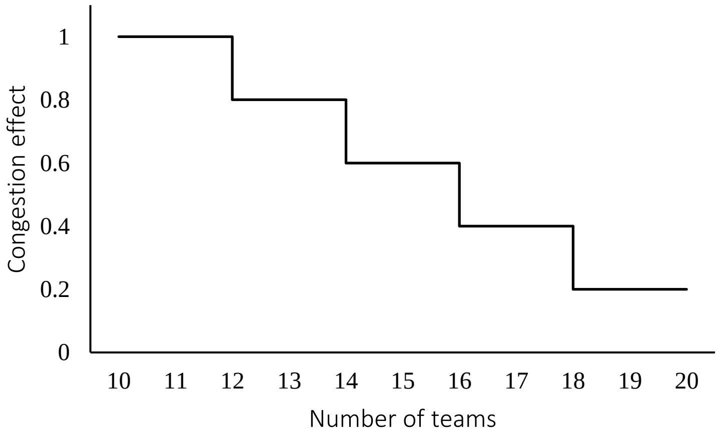
Table 4.3 Model validation with real data

	Real data	Simulated data
Average Demand	69.33 (0.27)	69.54 (0.25)
Average Volunteer Arrivals	30.66 (0.08)	31.29 (0.11)
Ratio: Inexp / Exp	2	2

*Standard error in parenthesis

Data input. Team performance over time depends on the congestion in the storehouse. The model assumes that the effect of congestion on the performance follows a step function, representing how teamwork is affected according to the number of teams picking at the same time. We know that the order preparation process works well as long as the number of teams is equal or lower than 12. In these cases, the teams work at 100% of their capacity. However, when there are over 18 teams in the storehouse at the same time, mobility is reduced and the model assumes a congestion effect equal to 0.2, which means that the teams can only work at 20% of their capacity, i.e. the time to process the order can increase up to 5 times in respect to its original value. Figure 4.4 captures the behavior of the congestion effect as a function of the number of teams in the storehouse.

Figure 4.4 Congestion effect on volunteer performance as a function of the number of teams in the storehouse



Submodels. *Volunteers arrive*. Reflecting the data observed in the storehouse during our participant observations, we simulate that 50% of the volunteers (both experienced and inexperienced) arrive at min 0, 10% at min 60, 30% at min 120 and the remaining 10% arrive at min 180.

Volunteers find a potential partner. In order to form a team, the other volunteer has to be alone, i.e. without a pair, and needs to match the criteria for pairing selected during the initialization step. In particular, if mixed volunteers arrive to the system, the pairing criteria to form a team would be mixed vs. no-mixed pairing. In some situations, in which the criteria cannot be followed due to lack of volunteers, the rule is overridden. For instance, if the model has a no-mixed pairing criterion, but there are only two volunteers of different experience left to be paired, then the no-mixed rule will be overlooked and the mixed volunteers will be considered as potential partners.

Volunteers form a team. After finding a suitable partner, volunteers form a new team according to the pairing strategy: Exp-Exp, Inexp-Inexp or Exp-Inexp. The experience level of the team is computed as an average of the individual levels, and the team is assigned the amount of orders to complete before leaving the system.

Volunteers find an incomplete order. As a team, volunteers look for an order to prepare. They follow this process until all orders are completed or until they leave the system.

Volunteers prepare the order. The process of preparing the order in the simulation does not involve physical movement; instead, it is represented by the use of time. While processing the order, the team remains in the same point with the order for as long as it takes to prepare it.

Volunteers get experience. After preparing an order, the teams learn and get experience of this process, increasing their experience level. The increase in the experience level follows a concave learning curve with an exponential function (Leibowitz, Baum, Enden, & Karniel, 2010) that allows a maximum value of 1,

$$E_n = 1 - (1 - E_0) * e^{-\propto * n}. \qquad (1)$$

Where E is the experience level, n is the number of orders volunteers complete, E_0 is the experience level before completing the first order, and $\propto$ is a constant rate coefficient with a value of 0.5.

Volunteers leave the storehouse. When the team completes the number of orders, one of the volunteers leaves according to the following rules. If the team is Exp-Exp, an experienced volunteer leaves and the other remains in the storehouse with 80% probability; both experienced volunteers leave with 20% probability. If the team is Inexp-Inexp, an inexperienced volunteer leaves and the other remains in the storehouse with 50% probability; both inexperienced volunteers leave with 50% probability. If the team is Exp-Inexp, an experienced volunteer remains in the storehouse with 50% probability, an inexperienced volunteer remains in the storehouse with 30% probability, and both leave with 20% probability.

Orders recompute processing time. Every time a team gets an order, the simulation model checks the level of both team experience and congestion to recompute the time that is going to take to complete the order, as per Equation (2).

$$PT = PT_0 * \left(\frac{1}{C}\right) * \left(\frac{1}{E}\right). \qquad (2)$$

Where PT is the processing time that the order will require, PT_0 is the initial processing time (i.e. 28 minutes), C is the congestion factor of the system (Figure 4.4) and E is the experience level of the team of volunteers that are going to work in the order.

System generates performance measures. For model analysis, two storehouse-level variables are recorded: on-time order preparation rate and additional time to prepare the orders. The storehouse manager expects to complete the order preparation process within five hours. Therefore, the first performance measure of the system is the proportion of orders completed at minute 300 (5 hours). Furthermore, as the simulation stops only when all the orders are prepared, the second performance measure we consider is the additional time (in minutes, after the first five hours) that the volunteers take to prepare all the orders.

4.3.4. Experimental Design

The experimental design consists of eight treatments and two scenarios. The experimental treatments come from a 4 x 2 design, which captures two factors influencing the operational performance of the supply chain. The first factor is volunteer experience and pairing. We model the situations where volunteers of a homogenous experience level arrive: only experienced or only inexperienced volunteers, who form teams among themselves. Then, we consider the cases of mixed arrivals, i.e. both experienced and inexperienced volunteers arrive in the storehouse, and we consider two kinds of pairing: mixed pairing (Exp-Inexp) and no-mixed pairing (Exp-Exp, Inexp-Inexp).

The second factor is congestion; we model the system allowing for and impeding congestion. The treatments with congestion allow pairing all the volunteers arriving in the storehouse, while the treatments without congestion are modeled under the rule that a maximum of 12 teams are allowed to be working in the order preparation process. Table 4.4 summarizes the 4 x 2 design.

Table 4.4 Experimental treatments

Treatments			
		Congestion	
		With	**Without**
Volunteer experience	Only experienced volunteers	T1	T2
	Only inexperienced volunteers	T3	T4
	A mix of experienced and inexperienced volunteers		
	Pairing: mixed (Exp-Inexp)	T5	T6
	Pairing: no mixed (Exp-Exp, Inexp-Inexp)	T7	T8

In addition to these treatments that allow a systematic comparison of the different policies affecting on-time order preparation, we contrast the results of two scenarios. The first one is the steady conditions, in which all the orders are prepared even if volunteers need to stay additional time in the storehouse. This scenario can be considered as ideal because demand is known, volunteer arrivals are controlled and there is never lost demand. Then, we simulate disaster scenarios under three different extreme conditions: (1) high demand, (2) high supply of volunteers and (3) high demand and high supply. We model the four different scenarios (baseline and three disaster conditions) and 32 treatments using NetLogo 6.0 (Northwestern University, Evanston, IL). Each result is the outcome of 2,000 runs.

4.4. Results

4.4.1. Scenario 1: Steady Conditions

The results for the scenario under steady conditions serve as an initial robustness check: the best operational performance for the supply chain is achieved when all the volunteers arriving in the storehouse are experienced, while the worst performance corresponds to the arrival of only inexperienced volunteers. However, when there is a mix of experience, the best performance corresponds to the mixed pairing. These results are consistent for the two performance measures: order preparation rate at minute 300 and additional time to prepare the orders. Table 4.5 summarizes the results for the performance measures in the 4 x 2 design.

The results of order preparation and additional time to complete the orders in Table 4.5 show that there are small (and non-statistically significant) differences between the treatments with congestion compared to the ones without congestion. Under steady conditions, the storehouse only experiences few periods with congestion, so few that they do not cause big differences in the output variables. Therefore, under this scenario, results show no difference between managerial policies that allow for congestion compared to those that impede it.

Table 4.5 Model results for on-time order preparation and additional time to complete orders

		Order preparation		Additional time (minutes)	
		Congestion		Congestion	
		With	Without	With	Without
	Only experienced volunteers arrive	0.98 (0.00)	0.98 (0.00)	16.34 (0.86)	17.01 (0.94)
	Only inexperienced volunteers arrive	0.80 (0.00)	0.81 (0.00)	154.81 (2.72)	157.13 (2.78)
Volunteer experience	A mix of experienced and inexperienced volunteers arrive				
	Pairing: mixed (Exp-Inexp)	0.88 (0.00)	0.88 (0.00)	106.29 (2.93)	106.42 (2.74)
	Pairing: no mixed (Exp-Exp, Inexp-Inexp)	0.87 (0.00)	0.87 (0.00)	119.86 (3.13)	125.75 (3.08)

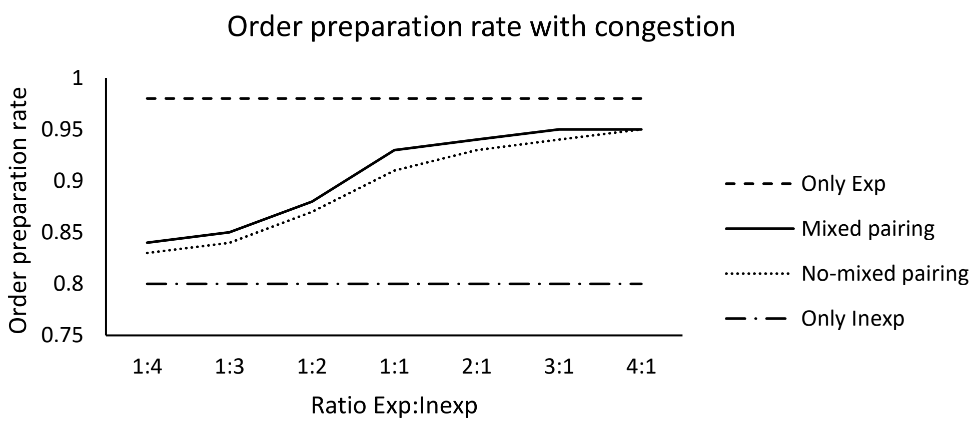
*Standard error in parenthesis

If we compare the effects of volunteer experience in the performance of the system, we observe that in the steady conditions with congestion having only experienced volunteers arriving in the storehouse increases the on-time order preparation rate from 80% to 98% (22.5% improvement) and reduces the additional time to complete the orders from 154 to 16 minutes (89.5% improvement) compared to the case when only inexperienced volunteers arrive. When a mix of experienced and inexperienced volunteers arrive in the storehouse, the results with congestion show that a mixed-pairing strategy improves the order preparation rate from 87% to 88% (1.2% increment) and reduces the additional time to complete the orders from 119 to 106 minutes (11.3% improvement) compared to no-mixed pairing.

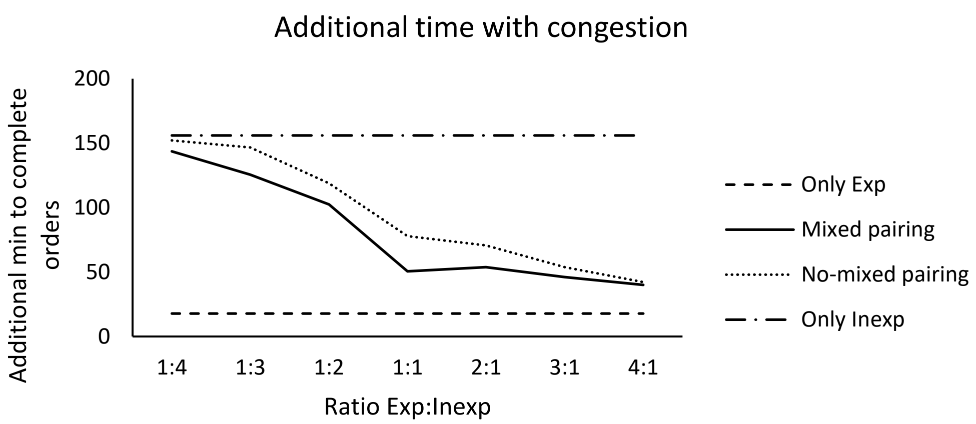
4.4.1.1. Sensitivity Analyses

We conduct sensitivity analyses on the experience ratio and learning curve. In general, we find that the initial results are robust to these changes. The first analysis consists of varying the ratio Exp:Inexp. In the original simulation, the ratio is 1:2 (one experienced for two inexperienced volunteers in the storehouse). Figure 4.5 shows graphically the results when changing the ratio from 1:4 to 4:1 with congestion (the results are similar for the policy without congestion).

Figure 4.5 Sensitivity analysis varying the ratio exp:inexp for (a) on-time order preparation and (b) additional time to complete the orders



(a)



(b)

After varying the ratio, the main finding is that the qualitative behavior of the performance does not change. The best results are always obtained with only experienced, followed by mixed pairing (which seems to benefit from a 1:1 ratio), no-mixed pairing and only inexperienced in the last position. In the extremes, we observe that the higher the amount of inexperienced arriving, the closer the behavior of the system to the "only Inexp" line; while the higher the amount of experienced, the closer the behavior to the "only Exp" line, but the lines never intersect. From an operational perspective, when the storehouse has mixed arrivals, the best strategy to pair the volunteers is always to follow a mixed pairing rule (Exp-Inexp).

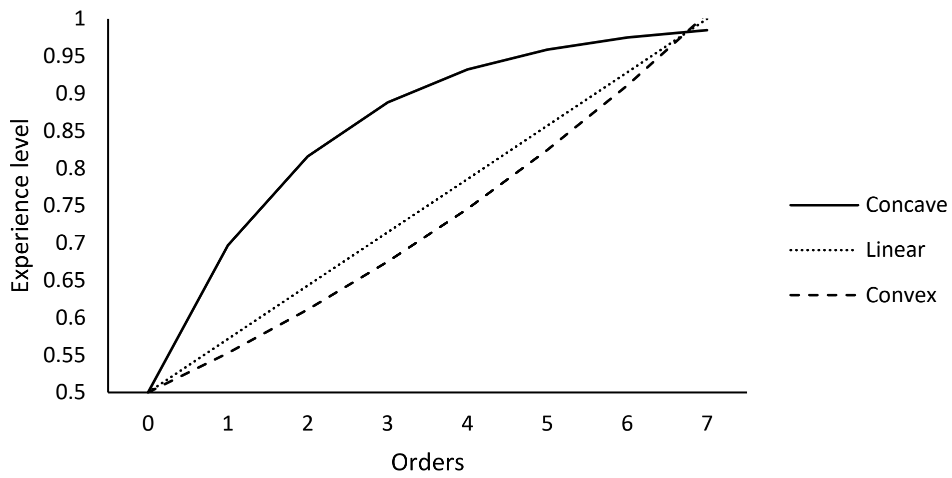
For the second sensitivity analysis varying the learning curves, we use three different functions: concave, linear and convex curves, and justify our choices as follows. The concave function is the same one we used in the scenario under steady conditions, following the formulation described in Equation (1) (Leibowitz et al., 2010). The linear function considers that the maximum amount of orders a volunteer will complete is seven and the slope depends on the initial experience level, so that the volunteer reaches the maximum experience level (one) with the maximum number of orders (seven). Equation (3) summarizes the formulation, where E_0 is the initial experience level and n is the number of orders completed.

$$E_n = \frac{1-E_0}{7} * n + E_0. \qquad (3)$$

Finally, we model the learning process as a convex curve, which follows an exponential growth (Anzanello & Fogliatto, 2011). Equation (4) shows the function we use for this curve, where the slope is adjusted so that the maximum value of experience level (one) is reached with the maximum number of orders (seven). Figure 4.6 shows the different functions for the case in which the initial experience level is 0.5.

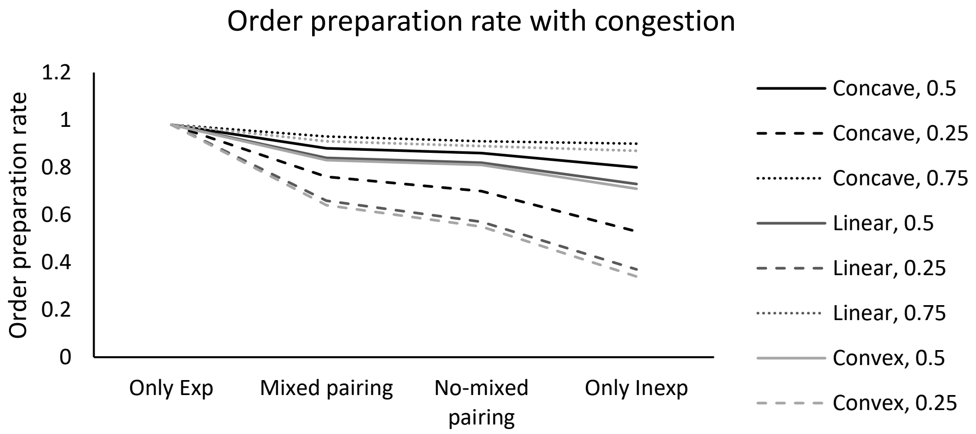
$$E_n = E_0 * e^{(slope*n)}. \qquad (4)$$

Figure 4.6 Learning curves for sensitivity analysis

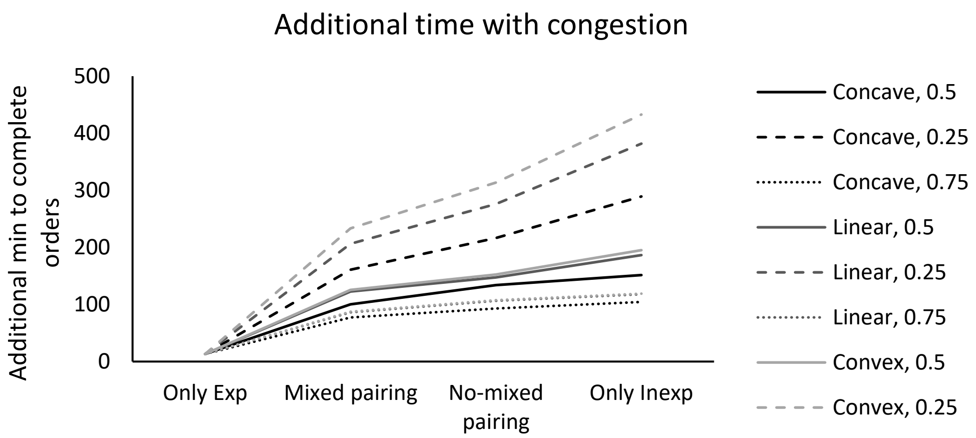


In addition to changing the learning curves, we also vary in the initial experience level of the inexperienced volunteers. In the original model this level is 0.5. We include two additional levels: 0.25 and 0.75. As an additional robustness check, we run the different learning curves considering the initial experience level of the inexperienced volunteers as 0.01. This extreme scenario assumes that volunteers are completely clueless about any of the processes taking place at the storehouse, which we find unrealistic. Results show that when inexperienced volunteers are the only ones arriving in the storehouse, the order preparation rate after five hours working in the storehouse will be zero. Similar to other results, we find that mixed pairing gives better results than no-mixed pairing for the order preparation rate. However, in all the cases in which inexperienced volunteers participate, the time to complete the orders is above 16 hours, which means that some of the demand would be lost. Figure 4.7 shows the results for the order preparation rate and the additional time to complete orders with the different variations for the treatments with congestion (results without congestion are similar).

Figure 4.7 Sensitivity analysis varying the type of learning curve and initial experience level for (a) on-time order preparation and (b) additional time to complete the orders



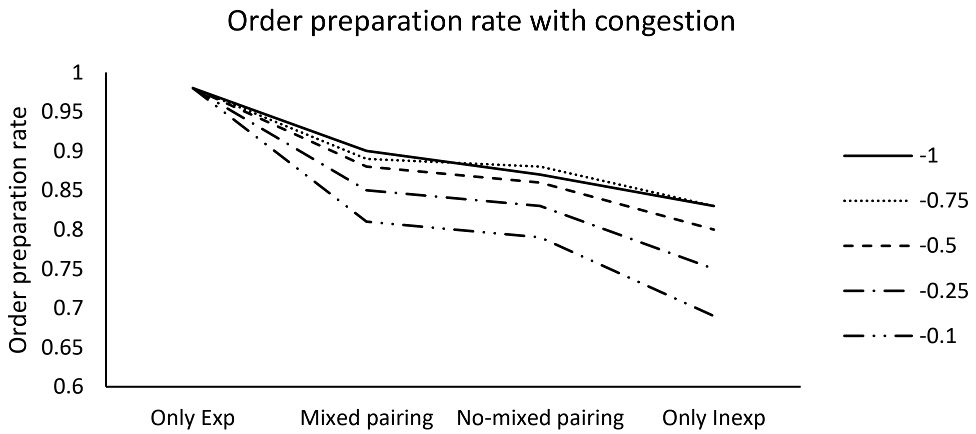
(a)



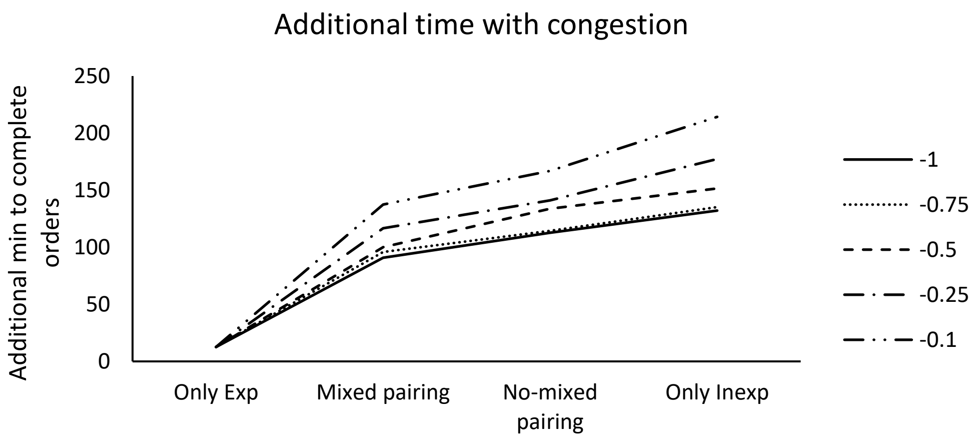
(b)

In this analysis, the treatment of “only exp” serves as a reference point because in this treatment no learning occurs. Results are robust to both the change of learning curves and the initial experience level. The best results are obtained with only experienced volunteers, followed by mixed pairing, no-mixed pairing and only inexperienced volunteers. Regarding the type of curve, the concave function gives the best results, followed by the linear function and finally the convex function. The initial experience level only adds variance to the range of values that can be obtained during the simulation, and it is always better to have a high initial level of experience. In the last analysis, we change the slope for the concave curve (i.e. the exponent in Equation (4)) to allow for different speeds in the learning process. Results for the treatments with congestion are shown in Figure 4.8. Similarly to the previous analysis, we observe that the qualitative behavior of the system is robust to the change of slopes for the concave curve.

Figure 4.8 Sensitivity analysis varying the slope for the concave function for (a) on-time order preparation and (b) additional time to complete the orders



(a)



(b)

4.4.2. Scenario 2: Disaster Conditions

In the second scenario, we study how the output variables, i.e. on-time order preparation rate and additional time to complete the orders, change as a function of increases in demand of orders and in supply of volunteers. We model the surges by a factor of three to simulate a disaster condition that can be challenging for the organization but still manageable. For the demand, we tripled the mean and the variance of the lognormal distribution of the orders used in the first scenario. For the supply of volunteers, we increased the number of volunteers arriving by three times. In this set of simulations, we assume that the organization has enough inventory to complete the orders processed by the volunteers, but the capacity of the storehouse does not change. Keeping the same capacity means that there is congestion in the storehouse when there are more than 12 teams of volunteers preparing orders.

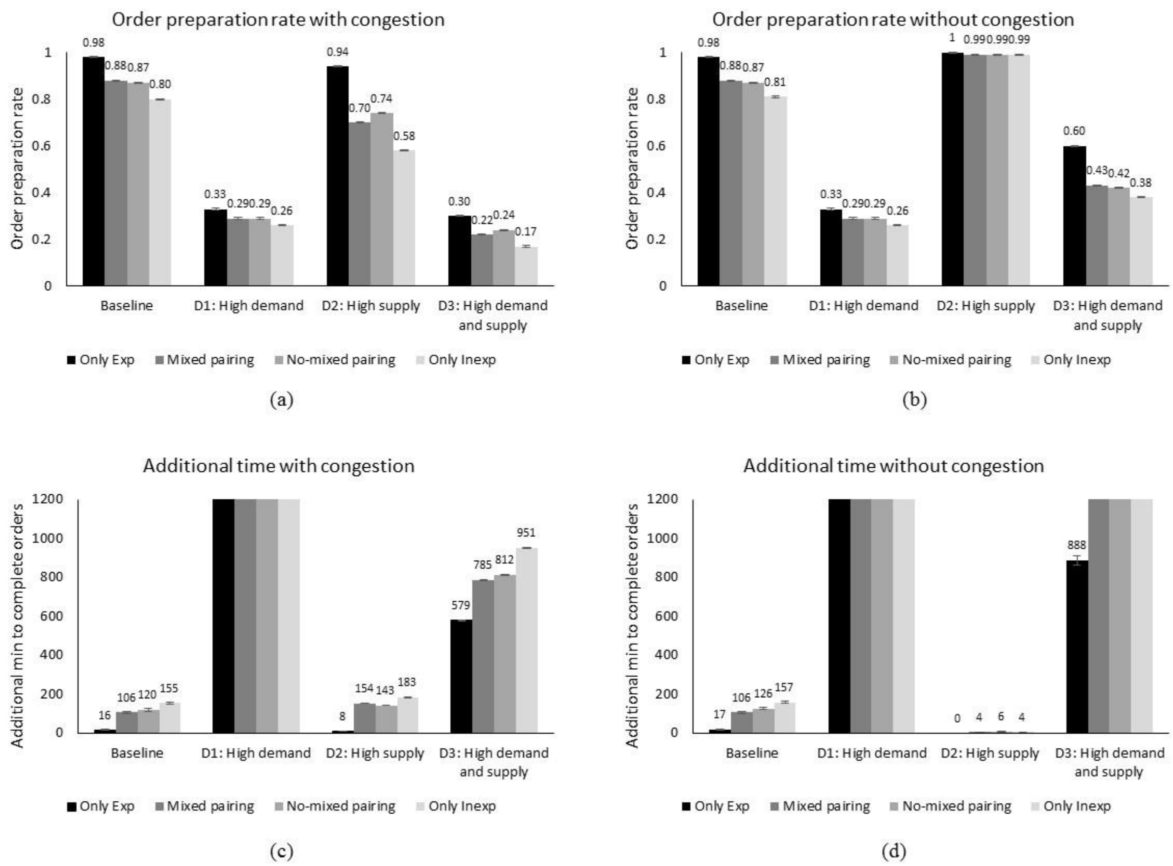
To model these changes systematically, we study three types of disaster conditions (D1, D2 and D3). The first simulation considers an increase only in the demand, maintaining the same amount of volunteers arriving as in the scenario of steady conditions (D1). This set of conditions reflect those disasters in which either the needs of the population surpasses the ability of any organization to respond or in which there is so little visibility that only a few volunteers arrive. An example of a situation with high demand of people in need and low supply of volunteers is the response in Puerto Rico after Hurricane Maria in 2017. Given the widespread nature of the disaster, one month after the island was struck, people were still waiting for help (Weir & Clarke, 2017). Second, we model a rise in the number of volunteers arriving in the storehouse while the distribution of the orders does not change (D2). In this case, we are considering disasters with high visibility in which the convergence of volunteers is very high, compared to the real need. One example of this situation is the convergence of volunteers after the World Trade Center attack in 2001; many people wanted to help, but given the concentrated nature of the disaster, only a reduced type and number of volunteers were actually needed (Kendra & Wachtendorf, 2001; Tierney, 2003). In the third simulation, we consider increases in both the demand for aid and the supply of volunteers (D3). These conditions reflect disasters with high need for volunteers and visibility, making volunteer convergence possible and necessary. For instance, after Superstorm Sandy, many people were able to help the most affected in different ways, from cleaning and rebuilding homes to developing communal activities to reconnect (CNN, 2012; Hughes, 2012).

Figure 4.9 shows the results for the different types of disaster conditions in a comparative way, including confidence intervals. Subfigures (a) and (b) refer to the on-time order preparation rate, while (c) and (d) correspond to the additional time to complete the orders. The first column shows the results with congestion and the second without congestion. The bars are colored according to the different experience levels and pairings of volunteers. Results show that when the storehouse receives both experienced and inexperienced volunteers, the gap between the pairing strategies reduces. In the condition D1, both mixed and no-mixed pairing strategies have the same performance for the order preparation rate. However, in the cases combining high supply of volunteers and congestion, the effects of the pairing strategies reverse: in the condition D2, the no-mixed pairing strategy improves the order preparation rate by 5.7% compared to the mixed-pairing strategy; while in the condition D3, the no-mixed pairing increases this performance measure by 9.1%. This shift in the performance of the pairing strategies is due to the higher availability of experienced volunteers in the storehouse when congestion is allowed. As experienced teams do not have to learn, the congestion in the storehouse has less effects on the speed of their order preparation. This situation makes the work of Exp-Exp teams more operationally efficient than combining them with inexperienced volunteers to facilitate collaboration and learning. Therefore, when there is a policy of allowing congestion combined with high supply of volunteers, the organization should follow a no-mixed pairing strategy.

Subfigures (a) and (c) indicate that when congestion is allowed in the storehouse, all the disaster conditions have a worse performance than the results for the steady conditions. In the steady conditions, the results for both performance measures do not change much when controlling for congestion because the number and rate of arrival of volunteers only allows for few periods with congestion. As the condition D1 keeps the same distribution for volunteer arrivals as the steady conditions, we find similar results on both outcome variables when we compare the first and second column of Figure 4.9. Therefore, under situations of only high demand, there are no differences between policies allowing for or impeding congestion. The main impact of high demand in the system is the deterioration of the performance measures: the on-time order preparation rate decreases and the additional time to complete the orders becomes so high (in the simulation, over 24 hours) that volunteers are not realistically able to finish all the orders, which means that demand will be lost.

In the condition D2, in which only the number of volunteers rise, results show that there is a loss of efficiency due to congestion. Allowing for congestion makes the on-time order preparation rate drop below 60% (when only inexperienced volunteers arrive), while impeding congestion increases this rate to almost 100% for all volunteer experience levels. We find similar results for the additional time to complete the orders: when there is no congestion, the additional time required is almost zero. Consequently, it seems that a policy that controls for congestion, limiting the quantity of volunteers working in the storehouse, is especially important when the number of volunteers exceeds the requirements imposed by the demand.

Figure 4.9 Model results for the three types of disaster conditions in comparison with the steady conditions



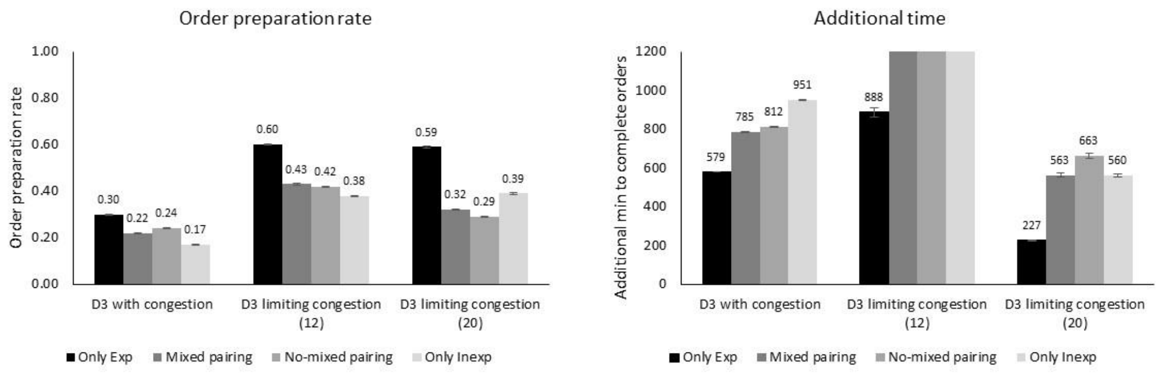
The condition D3 initially shows the same behavior with D2 regarding the inefficiencies congestion causes on the on-time order preparation rate. A comparison of subfigures (a) and (b) indicates that order preparation can double when impeding congestion. However, this growth comes at the cost of increasing the additional time to complete the orders. When congestion is not allowed, many volunteers are forced to leave the storehouse, which reduces the available supply to complete the orders. Therefore, the results show that when there is a combination of high demand and high supply of volunteers, limiting congestion might not be the best policy. It may improve the order preparation rate during the first 5 hours of operation, but in the long run it can damage the ability of the storehouse to complete the orders and demand can be lost.

4.4.3. Proposing a New Policy

As observed in the results for D3, completely limiting or allowing congestion may not be the best policies to follow during disaster conditions that involve high demand and high supply of volunteers. We argue that in these cases, implementing a more flexible policy that allows for some congestion in the storehouse may balance the trade-offs between the two extreme policies. Allowing for some congestion reduces the number of volunteers that are not allowed to enter the storehouse and increases the speed of the fully congested system. The policy that we propose is as follows: *Every time that the number of teams in the storehouse is below its capacity, allow some congestion.* In particular, we allow 8 additional teams over the 12 team capacity. This policy allows a fluctuating congestion over time: the first time that 20 teams enter the storehouse, the congestion is at its peak, but as teams' experience increases and some teams leave, the order preparation process speeds up. When the number of volunteers reduces below 12 and new teams enter, congestion affects all teams, but the experience acquired by the teams already in the storehouse helps reduce the process deceleration.

Figure 4.10 presents the results of the three policies for D3: allowing for congestion, impeding congestion (maximum 12 teams in the storehouse all the time) and allowing for some congestion (maximum 20 teams in the storehouse at some times). Results show that such an intermediate policy increases the on-time order preparation rates with respect to the case that allows congestion. Furthermore, the additional time to complete the orders reduces and reaches a level below both extreme policies of completely allowing or limiting congestion. Therefore, a more flexible policy has the potential to both improve the performance measures of the organization's supply chain and avoid the loss of demand.

Figure 4.10 Results of the three congestion policies for D3 respect to (a) on-time order preparation and (b) additional time to complete the orders



(a) (b)

4.5. Discussion

We use a multi-method approach, combining a case study with an agent-based simulation model, to provide evidence that volunteer experience and congestion can drive operational performance for organizations that rely heavily on volunteers to run their operations. We consider two operational performance measures for the supply chain: on-time order preparation rate and additional time to complete the orders.

We find that when humanitarian organizations manage volunteers with different experience levels, the best pairing strategy depends on the system conditions and that collaboration is not always the best choice. Under steady conditions, humanitarian organizations should follow a strategy of mixed-pairing (Exp-Inexp) because this strategy allows for knowledge exchange between the pair of volunteers. These results are consistent with the importance of training practices for volunteers (Lassiter et al., 2014, 2015) and with the positive effects of collaboration and information sharing previously reported in the literature (Siemsen et al., 2007; Urrea et al., 2016).

However, disaster scenarios may work as a boundary condition for the effectiveness of collaboration in supply chains. Congestion negatively affects the learning process of inexperienced volunteers. Under disaster conditions that combine congestion with high supply of volunteers, the no-mixed pairing strategy has better performance regarding on-time order preparation rate than the mixed-pairing strategy. The no-mixed pairing strategy has higher performance for two reasons. First, the high supply condition increases the availability of experienced volunteers in the storehouse. Second, as experienced teams do not have to learn, the congestion in the storehouse has less effects on the speed of their order preparation.

Our findings show that even if a system is adequately designed to be robust to the effects of congestion under a steady scenario, it might experience negative consequences during extreme or disaster conditions. In particular, we study three types of disaster conditions: high demand, high supply of volunteers, and both high demand and high supply. As the number of volunteers drives congestion in the storehouse, in the high-demand condition (when there is no increase in the number of volunteers) there are no differences between managerial policies that allow or impede congestion. However, these results are different for the cases in which we model a high supply of volunteers. In the high-supply condition, the policy that impedes congestion delivers the best operational results because it reduces the inefficiencies caused by exceeding the capacity of volunteers in the storehouse. In the high-demand high-supply condition, we find mixed results. Allowing congestion slows down the processes, which reduces the order preparation rate; while impeding congestion forces volunteers to leave the storehouse, impairing the capacity of the organization to complete the orders. We explore an alternative policy that allows for some congestion in the storehouse. We find that such a flexible policy works better because it balances the negative consequences of the extreme policies. It increases the speed of the fully congested storehouse and reduces the number of volunteers that are not allowed to enter the storehouse.

Our results not only enrich the literature on supply chain and volunteer management, but also have managerial implications for organizations that usually rely on volunteers to run their operations during both disaster response and steady conditions. On the one hand, under steady conditions inexperienced volunteers can benefit from the interaction with experienced ones. Building on these findings, humanitarian organizations should plan regular training sessions for their volunteers, and those trainings could be more efficient if they allow for social interaction. Humanitarian organizations should teach experienced volunteers how to train inexperienced ones to accelerate the learning process of the latter. Allowing for these mixed interactions in steady conditions can reduce the additional time to complete the orders. On the other hand, the managerial insights for the congestion policies are not straightforward. Humanitarian organizations need to evaluate the possible negative consequences of congestion policies that allow or impede congestion. Depending on the conditions, both policies may affect operational performance negatively. However, in situations with only high supply of volunteers, the negative consequences on the operational performance of the supply chain due to inefficiencies in the system should be highly weighted into the decision.

Given the nature of the ABS methodology, we are limited to study the behavioral consequences of policies that allow or impede congestion in the storehouse. For instance, when congestion is allowed, volunteers may dislike the experience and decide either to leave early or not come back in the future. On the contrary, when congestion is limited, volunteers that are not allowed to help may be discouraged and decide not to contribute more to the organization, neither with financial nor with time donations. Our current model is not intended to draw conclusions or recommend policies to minimize these kinds of behavioral-related issues of congestion policies. Future research on policies for adequate volunteer management can explore these behavioral aspects of congestion and include the evaluation of the impact of different training programs on the operational performance of humanitarian organizations.

Chapter 5. Conclusions

5.1. Findings

This dissertation examines the important relationship between HOs and donors, studying the different strategies that HOs can follow to access and manage donations from both institutional and private donors. **Chapter 2** follows an organizational perspective on donations to understand how HOs reduce uncertainty and access funding from institutional donors. Building on RDT and relational embeddedness, this chapter identifies two different types of strategies: (1) finding alternative donors in the same sector and region where the organization has expertise and (2) developing long-term relationships with donors. These strategies have different effects on the diversification efforts of HOs. HOs that strongly rely on finding alternative donors are less likely to diversify their operations in new geographical regions. Conversely, HOs that mainly rely on developing long-term relationships with donors are more likely to diversify in both new service sectors and new geographical regions. This difference on diversification can be explained by distinguishing between current and future uncertainty. While both strategies reduce the current uncertainty of accessing funds, only long-term relationships reduce future uncertainty. As HOs reduce future uncertainty by establishing a stable flow of resources from long-term donors, they obtain the flexibility needed to face more risk and move into new sectors and regions.

Chapter 3 follows an individual perspective on donations to understand how HOs access funding from private donors leveraging online crowdfunding platforms. This chapter shows that being transparent matters in trust-based contexts such as online crowdfunding for emergency response. Results show that both conventional transparency (via certification) and operational transparency (via work-related updates) are positively associated with donations. This means that crowdfunding campaigns that are certified and keep donors informed with updates can signal transparency to potential donors and increase donations. However, not all updates are the same. Operationally transparent updates (i.e., updates that use work-related words to describe the progress of the campaign) increase the trust of potential donors, which also reflects a rise of donations. Interestingly, the positive effects of operational transparency go beyond the benefits of conventional transparency. Therefore, in a crowdfunding setting, donors are more generous to campaigns that communicate the work performed with past donations than to campaigns certified by the government.

Chapter 4 follows an individual perspective on donations to understand how HOs manage time donations from private donors in a charity storehouse. This chapter uses a multi-method approach, combining a case study with an agent-based simulation model, to provide evidence that volunteer experience and congestion can drive operational performance for organizations that rely heavily on volunteers to run their operations. Results show that when humanitarian organizations manage volunteers with different experience levels, the best pairing strategy depends on the system conditions and that collaboration is not always the best choice. Under steady conditions, humanitarian organizations should follow a strategy of mixed-pairing because this strategy allows for knowledge exchange between the pair of volunteers. However, disaster scenarios may work as boundary conditions for the effectiveness of collaboration in supply chains, because congestion negatively affects the learning process of inexperienced volunteers. Under disaster conditions that combine congestion with high supply of volunteers, the no-mixed pairing strategy has better performance regarding on-time order preparation rate than the mixed-pairing strategy. These findings show that even if a system is adequately designed to be robust to the effects of congestion under a steady scenario, it might experience negative consequences during extreme or disaster conditions.

5.2. Contributions

The aggregated work of this dissertation contributes mainly to the humanitarian funding literature. However, each chapter also contributes to other research streams, such as RDT and transparency, and have different managerial implications. **Chapter 2** contributes to the literature on humanitarian funding by giving an active role to HOs in the process of accessing funding, which goes in contrast with established literature in humanitarian operations. Results show that HOs have an agency during the grant application process, which allows them to adopt different strategies both to access funding and to diversify their operations. This chapter also contributes to RDT: (1) by differentiating between current and future uncertainty and explain their link with strategies to reduce dependence, and (2) by studying the consequences of strategic actions on diversification.

Chapter 3 contributes to two streams of research: funding in humanitarian operations and transparency. First, it extends the literature on humanitarian funding by studying crowdfunding as a new online channel that organizations and individuals can use to raise funds from private donors. This chapter considers that private donors care about transparency and performance of emergency operations. Second, findings extend the literature on transparency by comparing two forms of information disclosure: conventional and operational transparency. The chapter studies the effect of conventional transparency (via governmental certification) and operational transparency (via work-related updates) on donations for crowdfunding campaigns targeted to emergencies. Therefore, individuals and organizations seeking to leverage online crowdfunding platforms can use work-related updates to increase donations above the certification effect or even to compensate for the lack of conventional transparency.

Chapter 4 enriches the literature on supply chain and volunteer management by moving away from research topics related to volunteer satisfaction and scheduling. The chapter adds to this literature by studying the effects of volunteer experience and congestion on two operational performance measures of the supply chain. Moreover, this chapter also has managerial implications for organizations that usually rely on volunteers to run their operations during both disaster response and steady conditions. On the one hand, HOs should teach experienced volunteers how to train inexperienced ones to accelerate the learning process of the latter. Allowing for these mixed interactions in steady conditions can reduce the additional time to complete the orders. On the other hand, the managerial insights for the congestion policies are not straightforward. Humanitarian organizations need to evaluate the possible negative consequences of congestion policies that allow or impede congestion. Depending on the conditions, both policies may affect operational performance negatively.

5.3. Future Research

This dissertation opens the doors for different extensions that could be addressed in future research. As a result from **Chapter 2**, future research can study other strategies at the dyadic level of the donor-HO relationship or follow the opposite perspective of the donor to understand what policies (if any) donors consider in the funding process. Beyond the humanitarian context, the arguments developed in this chapter can also extend to other business-to-business (B2B) settings in which it is difficult to develop bilateral strategies such as strategic alliances to secure future resources or in which solving current uncertainty does not necessarily solve future uncertainty. In these B2B contexts, future work can consider how the strategies or mechanisms that mitigate one type of uncertainty can affect the other or, extending this work, how reducing one type of uncertainty can influence other managerial decisions such as diversification.

Chapter 3 also has implications for future research. First, the higher positive effect of operational transparency over conventional transparency may be context dependent.

Future work can explore if conventional transparency has a different effect compared to operational transparency in slow-onset settings such as development programs. Second, researchers can consider website design decisions. In the crowdfunding platform under study, designers seem to give an increased emphasis (i.e., larger website space) to updates compared to the emphasis given to the certification process. When a campaign is certified, it appears as a relatively small tag in the campaign website. Therefore, future work can consider the impact of these kinds of design decisions on donations. Third, this empirical analysis only uses secondary data. Even if there were controls for the heterogeneity of campaigns and updates using fixed effects and coarsened exact matching, there are still limitations to the correct identification of the causal mechanisms. Future research could include experimental designs to investigate how much the results presented in this chapter are robust to other causal mechanisms such as the quality and type of images and videos included in the campaigns.

Chapter 4 opens avenues for future work on the behavioral consequences of policies that allow or impede congestion in the storehouse. For instance, when congestion is allowed, volunteers may dislike the experience and decide either to leave early or not come back in the future. On the contrary, when congestion is limited, volunteers that are not allowed to help may be discouraged and decide not to contribute more to the organization, neither with financial nor with time donations. Future research on policies for adequate volunteer management can explore these behavioral aspects of congestion and include the evaluation of the impact of different training programs on the operational performance of humanitarian organizations.

Bibliography

Abrahams, A. S., Fan, W., Wang, G. A., Zhang, Z., & Jiao, J. (2015). An integrated text analytic framework for product defect discovery. *Production and Operations Management*, *24*(6), 975–990. http://doi.org/10.1111/poms.12303

Abrahams, A. S., Jiao, J., Fan, W., Wang, G. A., & Zhang, Z. (2013). What's buzzing in the blizzard of buzz? Automotive component isolation in social media postings. *Decision Support Systems*, *55*(4), 871–882. http://doi.org/10.1016/j.dss.2012.12.023

Abrahams, A. S., Jiao, J., Wang, G. A., & Fan, W. (2012). Vehicle defect discovery from social media. *Decision Support Systems*, *54*(1), 87–97. http://doi.org/10.1016/j.dss.2012.04.005

Acimovic, J., & Goentzel, J. (2016). Models and metrics to assess humanitarian response capacity. *Journal of Operations Management*, *45*, 11–29. http://doi.org/10.1016/j.jom.2016.05.003

Aflaki, A., & Pedraza-Martinez, A. J. (2016). Humanitarian Funding in a Multi-Donor Market with Donation Uncertainty. *Production and Operations Management*, *25*(7), 1274–1291. http://doi.org/10.1111/poms.12563

Aldrich, H. E. (1979). *Organizations and environments*. Englewood Cliffs, NJ: Prentice-Hall.

Altay, N., & Pal, R. (2014). Information diffusion among agents: Implications for humanitarian operations. *Production and Operations Management*, *23*(6), 1015–1027. http://doi.org/10.1111/poms.12102

Amezcua, A. S., Grimes, M. G., Bradley, S. W., & Wiklund, J. (2013). Organizational sponsorship and founding environments: A contingency view on the survival of business-incubated firms, 1994-2007. *Academy of Management Journal*, *56*(6), 1628–

1654. http://doi.org/10.5465/amj.2011.0652

Andreoni, J. (1989). Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of Political Economy, 97*(6), 1447–1458. http://doi.org/10.1086/261662

Andreoni, J. (1990). Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal*, *100*(401), 464–477. http://doi.org/10.2307/2234133

Andreoni, J., Rao, J. M., & Trachtman, H. (2017). Avoiding the Ask: A Field Experiment on Altruism, Empathy, and Charitable Giving. *Journal of Political Economy*, *125*(3), 625–653. http://doi.org/10.1086/691703

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *Journal of Finance*, *59*(3), 1259–1294. http://doi.org/10.1111/j.1540-6261.2004.00662.x

Anzanello, M. J., & Fogliatto, F. S. (2011). Learning curve models and applications: Literature review and research directions. *International Journal of Industrial Ergonomics*, *41*(5), 573–583. http://doi.org/10.1016/j.ergon.2011.05.001

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, *57*(8), 1485–1509. http://doi.org/10.1287/mnsc.1110.1370

Bae, J., & Gargiulo, M. (2004). Partner Substitutability, Alliance Network Structure, and Firm Profitability in the Telecommunications Industry. *Academy of Management Journal*, *47*(6), 843–859. Retrieved from http://www.jstor.org/stable/20159626

Baker, W. E. (1990). Market Networks and Corporate Behavior. *American Journal of Sociology*, *96*(3), 589–625. Retrieved from http://www.jstor.org/stable/2781065

Balcik, B., Beamon, B. M., Krejci, C. C., Muramatsu, K. M., & Ramirez, M. (2010).

Coordination in humanitarian relief chains: Practices, challenges and opportunities. *International Journal of Production Economics*, *126*(1), 22–34. http://doi.org/10.1016/j.ijpe.2009.09.008

Barnett, C. (2015). Trends Show Crowdfunding To Surpass VC In 2016. *Forbes*. Retrieved from http://www.forbes.com/sites/chancebarnett/2015/06/09/trends-show-crowdfunding-to-surpass-vc-in-2016/

Barraket, J., Keast, R., Newton, C., Walters, K., & James, E. (2013). Spontaneous Volunteering During Natural Disasters. *The Australian Centre for Philanthropy and Nonprofit Studies, ACPNS61*, 1–58. Retrieved from www.qut.edu.au/business/acpns

Beamon, B. M., & Balcik, B. (2008). Performance measurement in humanitarian relief chains. *International Journal of Public Sector Management*, *21*(1), 4–25. http://doi.org/10.1108/09513550810846087

Beckman, C. M., & Haunschild, P. R. (2002). Network Learning: The Effects of Partners' Heterogeneity of Experience on Corporate Acquisitions. *Administrative Science Quarterly*, *47*(1), 92–124. http://doi.org/10.2307/3094892

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. (2004). Friends or Strangers? Firm-Specific Uncertainty, Market Uncertainty, and Network Partner Selection. *Organization Science*, *15*(3), 259–275. http://doi.org/10.1287/orsc.1040.0065

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing*, *29*(5), 585–609. http://doi.org/10.1016/j.jbusvent.2013.07.003

Besiou, M., Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2012). The Effect of Earmarked Funding on Fleet Management for Relief and Development. *INSEAD Working Paper No. 2012/10/TOM/INSEAD Social Innovation Centre*. http://doi.org/10.2139/ssrn.1991068

Besiou, M., Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2014). Vehicle supply chains in humanitarian operations: Decentralization, operational mix, and earmarked funding. *Production and Operations Management*, *23*(11), 1950–1965. http://doi.org/10.1111/poms.12215

Besiou, M., Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2018). OR applied to humanitarian operations. *European Journal of Operational Research*, *in press*.

Besiou, M., Stapleton, O., & Van Wassenhove, L. N. (2011). System dynamics for humanitarian operations. *Journal of Humanitarian Logistics and Supply Chain Management*, *1*(1), 78–103. http://doi.org/10.1108/20426741111122420

Besiou, M., & Van Wassenhove, L. N. (2015). Addressing the Challenge of Modeling for Decision-Making in Socially Responsible Operations. *Production and Operations Management*, *24*(9), 1390–1401. http://doi.org/10.1111/poms.12375

Borshchev, A., & Filippov, A. (2004). From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools. In *Proceedings of the 22nd International Conference of the System Dynamics Society* (pp. 1–23).

Brüntje, D., & Gajda, O. (Eds.). (2016). *Crowdfunding in Europe: State of the Art in Theory and Practice*. Springer International Publishing. http://doi.org/10.1007/978-3-319-18017-5

Buell, R. W., Kim, T., & Tsay, C.-J. (2017). Creating Reciprocal Value Through Operational Transparency. *Management Science*, *63*(6), 1673–1695. http://doi.org/10.1287/mnsc.2015.2411

Buell, R. W., & Norton, M. I. (2011). The Labor Illusion: How Operational Transparency Increases Perceived Value. *Management Science*, *57*(9), 1564–1579. http://doi.org/10.1287/mnsc.1110.1376

Buell, R. W., Porter, E., & Norton, M. I. (2016). *Surfacing the Submerged State:*

Operational Transparency Increases Trust in and Engagement with Government. *Harvard Business School Marketing Unit Working Paper No. 14-034*. Retrieved from https://ssrn.com/abstract=2349801

Burkart, C., Besiou, M., & Wakolbinger, T. (2016). The funding-Humanitarian supply chain interface. *Surveys in Operations Research and Management Science*, *21*(2), 31–45. http://doi.org/10.1016/j.sorms.2016.10.003

Calarco, J. M. (2011). "I Need Help!" Social Class and Children's Help-Seeking in Elementary School. *American Sociological Review*, *76*(6), 862–882. http://doi.org/10.1177/0003122411427177

Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach. *Decision Support Systems*, *50*(2), 511–521. http://doi.org/10.1016/j.dss.2010.11.009

Casciaro, T., & Piskorski, M. J. (2005). Power Imbalance, Mutual Dependence, and Constraint Absorption: A Closer Look at Resource Dependence Theory. *Administrative Science Quarterly*, *50*(2), 167–199. http://doi.org/10.2189/asqu.2005.50.2.167

Chandes, J., & Paché, G. (2010). Investigating humanitarian logistics issues: from operations management to strategic action. *Journal of Manufacturing Technology Management*, *21*(3), 320–340. http://doi.org/10.1108/17410381011024313

CNN. (2012). In Sandy's wake, help comes in unexpected ways. *CNN*. Retrieved from http://www.cnn.com/2012/11/29/us/sandy-good-deeds-irpt/index.html?iid=article_sidebar

Coleman, J. S. (1990). *Foundations of Social Theory*. Cambridge, MA: Belknap Press.

Davis, G. F., & Cobb, J. A. (2010). *Chapter 2 Resource Dependence Theory: Past and Future*. (C. B. Schoonhoven & F. Dobbin, Eds.)*Stanford's Organization Theory*

Renaissance, 1970–2000 (Research in the Sociology of Organizations, Volume 28). Emerald Group Publishing Limited. http://doi.org/10.1108/S0733-558X(2010)0000028006

De Bruecker, P., Van Den Bergh, J., Beliën, J., & Demeulemeester, E. (2015). Workforce planning incorporating skills: State of the art. *European Journal of Operational Research*, *243*(1), 1–16. http://doi.org/10.1016/j.ejor.2014.10.038

Decker, R., & Trusov, M. (2010). Estimating aggregate consumer preferences from online product reviews. *International Journal of Research in Marketing*, *27*(4), 293–307. http://doi.org/10.1016/j.ijresmar.2010.09.001

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, *84*(1), 151–161. http://doi.org/10.1162/003465302317331982

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424. http://doi.org/10.1287/mnsc.49.10.1407.17308

Dieleman, M., & Boddewyn, J. J. (2012). Using Organization Structure to Buffer Political Ties in Emerging Markets: A Case Study. *Organization Studies*, *33*(1), 71–95. http://doi.org/10.1177/0170840611430595

Drees, J. M., & Heugens, P. P. M. A. R. (2013). Synthesizing and Extending Resource Dependence Theory: A Meta-Analysis. *Journal of Management*, *39*(6), 1666–1698. http://doi.org/10.1177/0149206312471391

Ebrahim, A. (2005). Accountability myopia: Losing sight of organizational learning. *Nonprofit and Voluntary Sector Quarterly*. http://doi.org/10.1177/0899764004269430

Eckel, C. C., & Grossman, P. J. (1996). Altruism in Anonymous Dictator Games. *Games and Economic Behavior*, *16*(2), 181–191. http://doi.org/10.1006/game.1996.0081

Edwards, M., & Hulme, D. (1996). Too close for comfort? The impact of official aid on nongovernmental organizations. *World Development*, *24*(6), 961–973. http://doi.org/10.1016/0305-750X(96)00019-8

Eftekhar, M., Li, H., Van Wassenhove, L. N., & Webster, S. (2017). The role of media exposure on coordination in the humanitarian setting. *Production and Operations Management*, *26*(5), 802–816. http://doi.org/10.1111/poms.12669

Emerson, R. M. (1962). Power-Dependence Relations. *American Sociological Review*, *27*(1), 31–41. Retrieved from http://www.jstor.org/stable/2089716

Falasca, M., & Zobel, C. (2012). An optimization model for volunteer assignments in humanitarian organizations. *Socio-Economic Planning Sciences*, *46*(4), 250–260. http://doi.org/10.1016/j.seps.2012.07.003

Falasca, M., Zobel, C., & Ragsdale, C. (2011). Helping a small development organization manage volunteers more efficiently. *Interfaces*, *41*(3), 254–262. http://doi.org/10.1287/inte.1110.0570

Fehr, E., & Fischbacher, U. (2003). The nature of human altruism. *Nature*, *425*(6960), 785–791. http://doi.org/10.1038/nature02043

Fehr, E., & Gächter, S. (2002). Altruistic punishment in humans. *Nature*, *415*(6868), 137–140. http://doi.org/10.1038/415137a

Feinerer, I., & Hornik, K. (2012). tm: Text mining package. *R Package Version 0.5-7.1*, *1*(8).

Fink, G., & Redaelli, S. (2011). Determinants of International Emergency Aid-Humanitarian Need Only? *World Development*, *39*(5), 741–757. http://doi.org/10.1016/j.worlddev.2010.09.004

Fox, J. (2007). The uncertain relationship between transparency and accountability. *Development in Practice*, *17*(4–5), 663–671.

http://doi.org/10.1080/09614520701469955

Fritz, C. E., & Mathewson, J. . (1957). *Convergence behavior in disasters: A problem in social control. A special report prepared for the Committee on Disaster Studies.*

Froelich, K. A. (1999). Diversification of Revenue Strategies: Evolving Resource Dependence in Nonprofit Organizations. *Nonprofit and Voluntary Sector Quarterly*, *28*(3), 246–268. http://doi.org/10.1177/0899764099283002

Frumkin, P., & Keating, E. K. (2011). Diversification Reconsidered: The Risks and Rewards of Revenue Concentration. *Journal of Social Entrepreneurship*, *2*(2), 151–164. http://doi.org/10.1080/19420676.2011.614630

Gaventa, J., & McGee, R. (2013). The impact of transparency and accountability initiatives. *Development Policy Review*, *31*(S1), S3–S28. http://doi.org/10.1111/dpr.12017

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and Deterrents for Participation. *ACM Transactions on Computer-Human Interaction*, *20*(6), 34–66. http://doi.org/http://dx.doi.org/10.1145/2530540

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering*, *23*(10), 1498–1512. http://doi.org/10.1109/TKDE.2010.188

Gopal, R., Marsden, J. R., & Vanthienen, J. (2011). Information mining - Reflections on recent advancements and the road ahead in data, text, and media mining. *Decision Support Systems*, *51*(4), 727–731. http://doi.org/10.1016/j.dss.2011.01.008

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*(6), 1360–1380. http://doi.org/10.1086/225469

Gremler, D. D., & Gwinner, K. P. (2000). Customer-Employee Rapport in Service

Relationships. *Journal of Service Research*, *3*(1), 82–104. http://doi.org/10.1177/109467050031006

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., … DeAngelis, D. L. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological Modelling*, *198*(1–2), 115–126. http://doi.org/10.1016/j.ecolmodel.2006.04.023

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling*, *221*(23), 2760–2768. http://doi.org/10.1016/j.ecolmodel.2010.08.019

Grimmelikhuijsen, S., Porumbescu, G., Hong, B., & Im, T. (2013). The effect of transparency on trust in government: A cross-national comparative experiment. *Public Administration Review*, *73*(4), 575–586. http://doi.org/10.1111/puar.12047

Gulati, R. (1995). Social Structure and Alliance Formation Patterns: A Longitudinal Analysis. *Administrative Science Quarterly*, *40*(4), 619–652. Retrieved from http://www.jstor.org/stable/2393756

Gulati, R., & Gargiulo, M. (1999). Where Do Interorganizational Networks Come From? *American Journal of Sociology*, *104*(5), 1439–1493. http://doi.org/10.1086/210179

Gulati, R., & Sytch, M. (2007). Dependence Asymmetry and Joint Dependence in Interorganizational Relationships: Effects of Embeddedness on a Manufacturer's Performance in Procurement Relationships. *Administrative Science Quarterly*, *52*(1), 32–69. Retrieved from http://www.jstor.org/stable/20109902

Haavisto, I., & Goentzel, J. (2015). Measuring humanitarian supply chain performance in a multi-goal context. *Journal of Humanitarian Logistics and Supply Chain Management*, *5*(3), 300–324. http://doi.org/10.1108/JHLSCM-07-2015-0028

Hale, T. N. (2008). Transparency, accountability, and global governance. *Global*

Governance, *14*(1), 73–94. http://doi.org/10.2307/27800692

Harbaugh, W. T. (1998). What Do Donations Buy? A Model of Philanthropy Based on Prestige and Warm Glow. *Journal of Public Economics*, *67*, 269–284. http://doi.org/10.1016/S0047-2727(97)00062-5

Hashai, N. (2015). Within-industry diversification and firm performance - An S-shaped hypothesis. *Strategic Management Journal*, *36*(9), 1378–1400. http://doi.org/10.1002/smj.2290

Heide, J. B., & John, G. (1988). The Role of Dependence Balancing in Safeguarding Transaction-Specific Assets in Conventional Channels. *Journal of Marketing*, *52*(1), 20–35. http://doi.org/10.2307/1251683

Henrich, J., McElreath, R., Barr, A., Ensminger, J., Barrett, C., Bolyanatz, A., … Ziker, J. (2006). Costly Punishment across Human Societies. *Science*, *312*(5781), 1767–1770. http://doi.org/10.1126/science.1127333

Hilhorst, D. (2002). Being good at doing good? Quality and accountability of humanitarian NGOs. *Disasters*, *26*(3), 193–212. http://doi.org/10.1111/1467-7717.00200

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource Dependence Theory: A Review. *Journal of Management*, *35*(6), 1404–1427. http://doi.org/10.1177/0149206309343469

Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., Pérez, N., & Wachtendorf, T. (2014). Material Convergence: Important and Understudied Disaster Phenomenon. *Natural Hazards Review*, *15*(1), 1–12. http://doi.org/10.1061/(ASCE)NH.1527-6996.0000113

Holländer, H. (1990). A Social Exchange Approach to Voluntary Cooperation. *American Economic Review*, *80*(5), 1157–1167. http://doi.org/10.1126/science.151.3712.867-a

Howard, M. D., Withers, M. C., Carnes, C. M., & Hillman, A. J. (2016). Friends or strangers? It all depends on context: A replication and extension of Beckman, Haunschild, and Phillips (2004). In *Strategic Management Journal* (Vol. 37, pp. 2222–2234). http://doi.org/10.1002/smj.2573

Hughes, J. (2012). Volunteers help Sandy victims start over. *CNN*. Retrieved from http://www.cnn.com/2012/11/21/us/iyw-americares-volunteer/index.html?iid=article_sidebar

Hyndman, N., & McDonnell, P. (2009). Governance and charities: An exploration of key themes and development of a research agenda. *Financial Accountability & Management*, *25*(1), 5–31. http://doi.org/10.1111/j.1468-0408.2008.00463.x

Iacus, S. M., King, G., & Porro, G. (2009). CEM: Software for coarsened exact matching. *Journal of Statistical Software*, *30*(13), 1–27. http://doi.org/10.18637/jss.v030.i09

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361. http://doi.org/10.1198/jasa.2011.tm09599

Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, *20*(1), 1–24. http://doi.org/10.1093/pan/mpr013

Independent-Sector. (2016). *United for Charity: How Americans trust and value the charitable sector*. Washington D.C. Retrieved from https://www.independentsector.org/wp-content/uploads/2016/10/United-for-Charity-v5.pdf

IRS. (2018). Tax information for charities & other non-profits. Retrieved from https://www.irs.gov/charities-non-profits

Jenkin, M. (2015). Does voluntourism do more harm than good? *The Guardian*. Retrieved from https://www.theguardian.com/voluntary-sector-network/2015/may/21/western-volunteers-more-harm-than-good

Katila, R., Rosenberger, J. D., & Eisenhardt, K. M. (2008). Swimming with Sharks: Technology Ventures , Defense Mechanisms and Corporate Relationships. *Administrative Science Quarterly*, *53*(2), 295–332. Retrieved from http://www.jstor.org/stable/20109968

Keister, L. A. (2001). Exchange Structures in Transition: Lending and Trade Relations in Chinese Business Groups. *American Sociological Review*, *66*(3), 336–360. http://doi.org/10.2307/3088883

Kelly, E. F., & Stone, P. J. (1975). *Computer recognition of English word senses* (Vol. 13). North-Holland.

Kendra, J. M., & Wachtendorf, T. (2001). Rebel Food... Renegade Supplies: Convergence after the World Trade Center Attack. *University of Delaware, Disaster Research Center, 316*, 1–25.

Kessler, J. B., & Milkman, K. L. (2016). Identity in charitable giving. *Management Science*, 1–17. http://doi.org/10.1287/mnsc.2016.2582

Kim, H., Hoskisson, R. E., & Wan, W. P. (2004). Power dependence, diversification strategy, and performance in Keiretsu member firms. *Strategic Management Journal*, *25*(7), 613–636. Retrieved from http://www.jstor.org/stable/20142149

Kitts, J. A., Lomi, A., Mascia, D., Pallotti, F., & Quintane, E. (2017). Investigating the temporal dynamics of interorganizational exchange: Patient transfers among Italian hospitals. *American Journal of Sociology*, *123*(3), 850–910. http://doi.org/10.1086/693704

Kornish, L. J., & Hutchison-Krupat, J. (2017). Research on Idea Generation and Selection: Implications for Management of Technology. *Production and Operations Management*, *26*(4), 633–651. http://doi.org/10.1111/poms.12664

Kovács, G., & Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. *International Journal of Physical Distribution & Logistics Management*, *37*(2), 99–114. http://doi.org/10.1108/09600030710734820

Kraft, T., Valdés, L., & Zheng, Y. (2017). Supply chain visibility and social responsibility: Investigating consumers' behaviors and motives. *Manufacturing & Service Operations Management*, *in press*, 1–33. Retrieved from https://ssrn.com/abstract=2518627

Kunz, N., Van Wassenhove, L. N., McConnell, R., & Hov, K. (2015). Centralized vehicle leasing in humanitarian fleet management: the UNHCR case. *Journal of Humanitarian Logistics and Supply Chain Management*, *5*(3), 387–404. http://doi.org/10.1108/JHLSCM-07-2015-0034

Kuppuswamy, V., & L.Bayus, B. (2015). A Review of Crowdfunding Research and Findings. *SSRN Electronic Journal*. http://doi.org/10.2139/ssrn.2685739

Lacetera, N., Macis, M., & Slonim, R. (2014). Rewarding Volunteers: A Field Experiment. *Management Science*, *60*(5), 1107–1129. http://doi.org/10.1287/mnsc.2013.1826

Lassiter, K., Alwahishie, A., & Taaffe, K. (2014). Improving Volunteer Productivity and Retention during Humanitarian Relief Efforts. *Int. J Sup. Chain. Mgt*, *3*(2), 1–10.

Lassiter, K., Khademi, A., & Taaffe, K. M. (2015). A robust optimization approach to volunteer management in humanitarian crises. *International Journal of Production Economics*, *163*, 97–111. http://doi.org/10.1016/j.ijpe.2015.02.018

Lattimer, C., Swithern, S., Sparks, D., Tuchel, L., Evans, H., Johnson, M., … Wasiuk, D. (2017). *Global Humanitarian Assistance Report 2017*. Retrieved from http://reliefweb.int/report/world/global-humanitarian-assistance-report-2017

Lee, J. Y., Swink, M., & Pandejpong, T. (2011). The roles of worker expertise, information sharing quality, and psychological safety in manufacturing process innovation: An intellectual capital perspective. *Production and Operations Management*, *20*(4), 556–570. http://doi.org/10.1111/j.1937-5956.2010.01172.x

Lee, S. H., Mun, H. J., & Park, K. M. (2015). When is dependence on other organizations burdensome? The effect of asymmetric dependence on internet firm failure. *Strategic Management Journal*, *36*(13), 2058–2074. http://doi.org/10.1002/smj.2330

Leibowitz, N., Baum, B., Enden, G., & Karniel, A. (2010). The exponential learning equation as a function of successful trials results in sigmoid performance. *Journal of Mathematical Psychology, 54*(3), 338–340. http://doi.org/10.1016/j.jmp.2010.01.006

Leiras, A., de Brito Jr, I., Queiroz Peres, E., Rejane Bertazzo, T., & Tsugunobu Yoshida Yoshizaki, H. (2014). Literature review of humanitarian logistics research: trends and challenges. *Journal of Humanitarian Logistics and Supply Chain Management*, *4*(1), 95–130. http://doi.org/10.1108/JHLSCM-04-2012-0008

Levinthal, D. A., & Fichman, M. (1988). Dynamics of Interorganizational Attachments: Auditor-Client Relationships. *Administrative Science Quarterly*, *33*(3), 345–369. http://doi.org/10.2307/2392713

Li, F. (2010). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature*, *29*, 143–165.

Li, N., & Wu, D. D. (2010). Using text mining and sentiment analysis for online forums hotspot detection and forecast. *Decision Support Systems*, *48*(2), 354–368. http://doi.org/10.1016/j.dss.2009.09.003

Lindenberg, M. (2001). Are We at the Cutting Edge or the Blunt Edge? Improving NGO Organizational Performance with Private and Public Sector Strategic Management Frameworks. *Nonprofit Management and Leadership*, *11*(3), 247–270. http://doi.org/10.1002/nml.11302

Lodree, E. J., & Davis, L. B. (2016). Empirical analysis of volunteer convergence following the 2011 tornado disaster in Tuscaloosa, Alabama. *Natural Hazards*, *84*(2), 1109–1135. http://doi.org/10.1007/s11069-016-2477-8

Loughran, T., & Mcdonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance*, *66*(1), 35–65. http://doi.org/10.1111/j.1540-6261.2010.01625.x

Lubatkin, M., Merchant, H., & Srinivasan, N. (1993). Construct validity of some unweighted product-count diversification measures. *Strategic Management Journal*, *14*(6), 433–449. http://doi.org/10.1002/smj.4250140604

Luker, K. (1984). *Abortion and the Politics of Motherhood*. Berkeley: University of California Press. http://doi.org/10.1111/1467-9566.ep10958194

Mayorga, M. E., Lodree, E. J., & Wolczynski, J. (2017). The optimal assignment of spontaneous volunteers. *Journal of the Operational Research Society*, *68*(9), 1106–1116. http://doi.org/10.1057/s41274-017-0219-2

McDougall, G. H. G., & Levesque, T. (2000). Customer satisfaction with services: Putting perceived value into the equation. *Journal of Services Marketing*, *14*(5), 392–410. http://doi.org/http://dx.doi.org/10.1108/08876040010340937

Natarajan, K. V, & Swaminathan, J. M. (2014). Inventory management in humanitarian operations: Impact of amount, schedule, and uncertainty in funding. *Manufacturing & Service Operations Management*, *16*(4), 595–603. http://doi.org/10.1287/msom.2014.0497

Nelson, R. R., & Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Cambridge: Belknap Press/Harvard University Press.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521–543. http://doi.org/10.1287/mksc.1120.0713

Neuendorf, K. A. (2017). *The content analysis guidebook*. *The Content Analysis Guidebook* (2nd editio). Los Angeles: Sage.

Nienhüser, W. (2008). Resource Dependence Theory - How Well Does It Explain Behavior of Organizations? *Management Revue*, *19*(1/2), 9–32. Retrieved from http://www.jstor.org/stable/41783569

OECD. (2017). OECD.Stat. Retrieved July 31, 2017, from http://stats.oecd.org/Index.aspx?QueryId=58192

Oloruntoba, R., & Gray, R. (2006). Humanitarian aid: an agile supply chain? *Supply Chain Management: An International Journal*, *11*(2), 115–120. http://doi.org/10.1108/13598540610652492

Olson, M. (1965). *The logic of collective action*. Cambridge: Harvard University Press. http://doi.org/10.1007/978-3-319-20451-2_32

Pedraza-Martinez, A. J., Stapleton, O., & Van Wassenhove, L. N. (2011). Field vehicle fleet management in humanitarian operations: A case-based approach. *Journal of Operations Management*, *29*(5), 404–421. http://doi.org/10.1016/j.jom.2010.11.013

Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2016). Empirically grounded research in humanitarian operations management: The way forward. *Journal of Operations Management*, *45*, 1–10. http://doi.org/10.1016/j.jom.2016.06.003

Pfeffer, J., & Salancik, G. R. (1978). *The External Control of Organizations: A Resource Dependence Perspective*. New York: Harper & Row.

Podolny, J. M. (1993). A Status-Based Model of Market Competition. *American Journal of Sociology*, *98*(4), 829–872. http://doi.org/10.1007/sl0551-01

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology. *Administrative Science Quarterly*, *41*(1), 116–145. http://doi.org/10.2307/2393988

Prouteau, L., & Wolff, F. C. (2008). On the relational motive for volunteer work. *Journal of Economic Psychology*, *29*(3), 314–335. http://doi.org/10.1016/j.joep.2007.08.001

R Development Core Team. (2000). *R Language Definition*. Viena, Austria: R foundation for statistical computing.

Rao, H. (1994). The Social Construction of Reputation: Certification Contests, Legitimation, and the Survival of Organizations in the American Automobile Industry: 1895–1912. *Strategic Management Journal*, *15*, 29–44. http://doi.org/10.1002/smj.4250150904

Rao, H., & Sivakumar, K. (1999). Institutional Sources of Boundary-Spanning Structures: The Establishment of Investor Relations Departments in the Fortune 500 Industrials. *Organization Science*, *10*(1), 27–42. http://doi.org/10.1287/orsc.10.1.27

Raschky, P. A., & Schwindt, M. (2012). On the channel and type of aid: The case of international disaster assistance. *European Journal of Political Economy*, *28*(1), 119–131. http://doi.org/10.1016/j.ejpoleco.2011.07.001

Rogan, M. (2014). Too Close for Comfort? The Effect of Embeddedness and Competitive Overlap on Client Relationship Retention Following an Acquisition. *Organization Science*, *25*(1), 185–203. http://doi.org/10.1287/orsc.2013.0833

Rogan, M., & Greve, H. R. (2015). Resource Dependence Dynamics: Partner Reactions to Mergers. *Organization Science*, *26*(1), 239–255. http://doi.org/10.1287/orsc.2014.0897

Rumelt, R. P. (1982). Diversification strategy and profitability. *Strategic Management Journal*, *3*(4), 359–369. http://doi.org/10.1002/smj.4250030407

Ryzhov, I. O., Han, B., & Bradić, J. (2016). Cultivating disaster donors using data analytics. *Management Science*, *62*(3), 849–866. http://doi.org/10.1287/mnsc.2015.2149

Sampson, S. E. (2006). Optimization of volunteer labor assignments. *Journal of Operations Management*, *24*(4), 363–377. http://doi.org/10.1016/j.jom.2005.05.005

Scarpin, M. R. S., & De Oliveira Silva, R. (2014). Humanitarian logistics: Empirical evidences from a natural disaster. *Procedia Engineering*, *78*, 102–111. http://doi.org/10.1016/j.proeng.2014.07.045

Schumaker, R. P., & Chen, H. (2009). Textual analysis of stock market prediction using breaking financial news: The AZFin text system. *ACM Transactions on Information Systems (TOIS)*, *27*(2), 1–19. http://doi.org/10.1145/1462198.1462204

Scott, W., & Davis, G. (2007). *Organizations and organizing: Rational, natural and open systems perspectives*. Upper Saddle River, NJ: Prentice Hall.

Shmueli, G., Bruce, P. C., & Patel, N. R. (2016). *Data mining for business analytics: Concepts, techniques, and applications with XLMiner* (3rd editio). Hoboken, New Jersey: John Wiley and Sons Inc.

Siemsen, E., Balasubramanian, S., & Roth, A. V. (2007). Incentives That Induce Task-Related Effort, Helping, and Knowledge Sharing in Workgroups. *Management Science*, *53*(10), 1533–1550. http://doi.org/10.1287/mnsc.1070.0714

Starr, M. K., & Van Wassenhove, L. N. (2014). Introduction to the Special Issue on Humanitarian Operations and Crisis Management. *Production and Operations Management*, *23*(6), 925–937. http://doi.org/10.1111/poms.12227

Stauffer, J. M., Pedraza-Martinez, A. J., & Van Wassenhove, L. N. (2016). Temporary hubs for the global vehicle supply chain in humanitarian operations. *Production and Operations Management*, *25*(2), 192–209. http://doi.org/10.1111/poms.12427

Stearns, T. M., Hoffman, A. N., & Heide, J. B. (1987). Performance of commercial television stations as an outcome of interorganizational linkages and environmental conditions. *Academy of Management Journal*, *30*(1), 71–90.

http://doi.org/10.2307/255896

Stephenson, M. (2005). Making humanitarian relief networks more effective: Operational coordination, trust and sense making. *Disasters*, *29*(4), 337–350. http://doi.org/10.1111/j.0361-3666.2005.00296.x

Stephenson, M., & Schnitzer, M. H. (2006). Interorganizational Trust, Boundary Spanning, and Humanitarian Relief Coordination. *Nonprofit Management & Leadership*, *17*(2), 211–233. http://doi.org/10.1002/nml

Stone, P. J., Dunphy, D. C., Smith, M. S., & Ogilvie, D. M. (1966). *General inquirer: A computer approach to content analysis*. MIT Press. http://doi.org/10.2307/2092070

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*(1), 1–21. http://doi.org/10.1214/09-STS313

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *Journal of Finance*, *63*(3), 1437–1467. http://doi.org/10.1111/j.1540-6261.2008.01362.x

Thomas, A. S., & Kopczak, L. R. (2005). *From Logistics to Supply Chain Management: The Path Forward in the Humanitarian Sector*. San Francisco. Retrieved from http://www.fritzinstitute.org/PDFs/WhitePaper/FromLogisticsto.pdf

Thompson, J. D. (1967). *Organizations in action: Social science bases of administrative theory*. *Transaction Publishers*. New York: McGraw-Hill. http://doi.org/{{{doi}}}

Tierney, K. J. (2003). Conceptualizing and Measuring Organizational and Community Resilience: Lessons from the Emergency Response Following the September 11, 2001 Attack on the World Trade Center. *(Preliminary Paper)*, 1–8. Retrieved from http://udspace.udel.edu/handle/19716/735

Tomasini, R. M., & Van Wassenhove, L. N. (2009). From preparedness to partnerships: case study research on humanitarian logistics. *International Transactions in*

Operational Research, *16*(5), 549–559. http://doi.org/10.1111/j.1475-3995.2009.00697.x

Toyasaki, F., & Wakolbinger, T. (2014). Impacts of earmarked private donations for disaster fundraising. *Annals of Operations Research*, *221*(1), 427–447. http://doi.org/10.1007/s10479-011-1038-5

Urrea, G., Villa, S., & Gonçalves, P. (2016). Exploratory analyses of relief and development operations using social networks. *Socio-Economic Planning Sciences*, *56*, 27–39. http://doi.org/10.1016/j.seps.2016.05.001

Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review*, *61*(4), 674–698. http://doi.org/10.2307/2096399

Uzzi, B. (1997). Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly*, *42*(1), 35–67. Retrieved from http://www.jstor.org/stable/2393808

Van Wassenhove, L. N. (2006). Humanitarian aid logistics: supply chain management in high gear. *Journal of the Operational Research Society*, *57*(5), 475–489. http://doi.org/10.1057/palgrave.jors.2602125

Van Wassenhove, L. N., & Pedraza-Martinez, A. J. (2012). Using OR to adapt supply chain management best practices to humanitarian logistics. *International Transactions in Operational Research*, *19*, 307–322. http://doi.org/10.1111/j.1475-3995.2010.00792.x

Villa, S., Odong, T., & Gonçalves, P. (2017). Understanding the contribution of effective communication strategies to program performance in humanitarian organizations. *Journal of Humanitarian Logistics and Supply Chain Management*, *7*(2), 1–25.

Wachtendorf, T., & Kendra, J. M. (2004). Considering Convergence, Coordination, and

Social Capital in Disasters. *University of Delaware, Disaster Research Center*, *342a*, 1–19.

Wakolbinger, T., & Toyasaki, F. (2014). *Impacts on funding systems on humanitarian operations*. (P. Tatham & M. Christopher, Eds.) (2nd ed.). Kogan Page.

Weir, B., & Clarke, R. (2017). War veterans deploy themselves to help Puerto Rico relief. *CNN*. Retrieved from http://www.cnn.com/2017/10/19/us/puerto-rico-veteran-volunteers/index.html

Whittaker, J., McLennan, B., & Handmer, J. (2015). A review of informal volunteerism in emergencies and disasters: Definition, opportunities and challenges. *International Journal of Disaster Risk Reduction*, *13*, 358–368. http://doi.org/10.1016/j.ijdrr.2015.07.010

Willems, J., & Walk, M. (2013). Assigning volunteer tasks: The relation between task preferences and functional motives of youth volunteers. *Children and Youth Services Review*, *35*(6), 1030–1040. http://doi.org/10.1016/j.childyouth.2013.03.010

Wisner, P. S., Stringfellow, A., Youngdahl, W. E., & Parker, L. (2005). The service volunteer - Loyalty chain: An exploratory study of charitable not-for-profit service organizations. *Journal of Operations Management*, *23*(2), 143–161. http://doi.org/10.1016/j.jom.2004.07.003

Wry, T., Cobb, J. A., & Aldrich, H. E. (2013). More than a Metaphor: Assessing the Historical Legacy of Resource Dependence and its Contemporary Promise as a Theory of Environmental Complexity. *The Academy of Management Annals*, *7*(1), 441–488. http://doi.org/10.1080/19416520.2013.781862

Xia, J., & Li, S. (2013). The divestiture of acquired subunits: A resource dependence approach. *Strategic Management Journal*, *34*(2), 131–148. http://doi.org/10.1002/smj.2008

Xiang, X., Kennedy, R., & Madey, G. (2005). Verification and Validation of Agent-based Scientific Simulation Models. *Agent-Directed Simulation Conference*, 47–55. Retrieved from http://www.nd.edu/~nom/Papers/ADS019_Xiang.pdf