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Raising funds in the era of digital economy

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RAISING FUNDS IN THE ERA OF DIGITAL ECONOMY

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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
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Raising Funds in the Era of Digital Economy

Deserina Sulaeman

Abstract

The rapid advancement in technology and internet penetration have substantially increased the number of economic transactions conducted online. Platforms that connect economic agents play an important role in this digital economy. The unbridled proliferation of digital platforms calls for a closer examination of the factors that could affect the welfare of the increasing number of economic agents who participate in them.

This dissertation examines the factors that could affect the welfare of agents using the setting of a crowdfunding platform where fundraisers develop campaigns to solicit funding from potential donors. These factors can be broadly categorized into three distinct groups: (1) campaign and its corresponding fundraiser characteristics, (2) other factors within the platform, and (3) other factors outside the platform. The first group of factors has been examined in a large number of studies. The second and third groups, which encompass factors external to the campaigns and fundraisers remain under-explored and therefore are the focus of this dissertation.

The first essay in this dissertation explores a factor within the platform; how displaying certain campaigns more prominently on the platform affects the performance of other campaigns. Such selective prominent practice is often viewed negatively because it is perceived to place less prominent sellers at a disadvantage (Kramer & Schnurr, 2018). The findings from the first essay provide a counterpoint to this popular view by documenting a positive spill-over effect from an increase in

the performance of the prominent campaigns. In particular, when the prominent campaigns perform well, market expansion occurs with more donors entering the platform, benefiting the less prominent campaigns. These findings mitigate the concern that non-neutral practices on digital platforms naturally lead to the rich getting richer and the poor getting poorer.

The second essay explores a factor external to the platform; how public statements from a government official affect private donations to charitable crowdfunding campaigns. A clear pattern of ethnic homophily among fundraisers and donors, where Hispanic fundraisers receive disproportionately more donations from Hispanic donors, is observed in this setting. This pattern of homophily becomes stronger following statements from President Donald Trump. This essay documents how social media usage, particularly by a government official, can influence the dynamic within and across ethnic groups. In sum, the findings from the two essays help inform platform designers, policymakers, and government officials of the potential effects of their actions on the digital economy.

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In memory of my father

Thank you for being the first and most important teacher in my life

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To my daughter

Thank you for the hugs and kisses that always lift my spirit up

Chapter 1 - Introduction

The advancement in technologies and rapid adoption of the internet in recent decades have fuelled the growth of the digital economy, where economic activities are conducted as a result of online connection among agents in the market. Indeed, the size of the digital economy in the US reached $1.35 trillion (6.9% of the US GDP) in 2017 and it is expected to continue to grow rapidly (Bureau of Economic Analysis, 2019). Platforms that connect the different economic agents play a key role in the digital economy as they often act as gatekeepers for access to contents and trades on the internet (European Commission, 2017; Kenney & Zysman, 2016; Morvan, Hintermann, & Vazirani, 2016). The continuing proliferation of these digital platforms calls for a closer examination into the factors that could affect the welfare of the economic agents who use these platforms.

I use the setting of crowdfunding platforms to study the different factors that could affect the welfare of the economic agents participating in digital platforms. The factors that could influence the success of crowdfunding campaigns can be broadly categorized into three groups: (1) campaign- and fundraiser-specific factors, (2) factors from within the platforms, and (3) factors from outside the platform.

A large literature on the first group of factors, including a study by Sulaeman & Lin (2018), documents campaign- and fundraiser-specific characteristics that influence the performance of crowdfunding campaigns. For instance, Johnson, Stevenson, and Letwin (2018) examines the role of gender in the success of a crowdfunding campaign. A study by Mollick (2014) documents that the time and efforts taken by fundraisers to craft their campaigns, proxied by the use of video in the campaign, how often they post updates, and the number of spelling errors in the project descriptions, can affect the success of their crowdfunding campaigns.

Another example is a study by Lin, Prabhala, and Viswanathan (2013) that documents the effect of a fundraisers' friendship networks on the success of their crowdfunding campaigns. In contrast, the factors external to the campaigns and fundraisers themselves, remain under-explored. This dissertation consists of two essays that examine factors from within the platform and from outside the platform, which encompass factors from the second and third groups.

The two essays in this dissertation utilize the setting of charitable campaigns on a crowdfunding platform. The datasets utilized in the empirical analyses were collected from charitable campaigns on *GoFundMe*, one of the largest charity-focused crowdfunding platforms (Mercer, 2016). Crowdfunding platforms like GoFundMe allow fundraisers, even those with limited experience, to solicit a large set of potential donors at a relatively low fundraising costs.[1] Therefore, it is not surprising that more and more fundraisers turn to crowdfunding platforms as a viable channel for fundraising. On GoFundMe, fundraisers do not promise any rewards in the form of repayment, goods, or equity to donors who contributed to their campaigns as the platform operates as a *donation-based* crowdfunding platform. Moreover, the platform employs a *Keep-it-All* payment model in which fundraisers receive the entire amount of donation raised (less fees) regardless of reaching their respective funding goals.

In the first essay, I ask the question of how platforms' non-neutral practices affect the performance of the campaigns on crowdfunding platforms. Given the important role played by online platforms as gatekeepers in the digital economy,

[1] At the time of data collection, GoFundMe charged 5% platform fee and 2.5% +$0.30/donation payment processing fee for the donations received by fundraisers on its platform. In 2018, after the data collection period, GoFundMe changed its fee structure. Currently, it does not charge the platform fee for campaigns started by individual fundraisers anymore, instead it relies on voluntary tips from donors to generate its revenue.

many concerns have been raised regarding how the practices utilized by these platforms affect the welfare of the economic agents who use them. The first essay aims to shed some light on the debate of whether non-neutral practices on digital platforms would lead to an outcome that over time would negatively affect trades in the digital economy (Kim, 2018; Kramer & Schnurr, 2018).

One important concern is regarding the order of how sellers, or fundraisers in the crowdfunding context, are listed on these platforms (European Commission, 2017; Kramer & Schnurr, 2018). The concern is that sellers that are listed less prominently on the platform could be placed at a disadvantageous position as potential buyers may only consider sellers that are more visible to them (Animesh, Viswanathan, & Agarwal, 2011; Breugelmans, Campo, & Gijsbrechts, 2007; Jeziorski & Moorthy, 2018). Consequently, buyers' choice may be limited to only the more prominent sellers because buyers may not consider the full set of sellers in their decision making process (Kramer & Schnurr, 2018).

The findings from the first essay show a positive spill-over effect from the exceptional performance of the more prominent campaigns. In particular, when the prominent campaigns perform exceptionally well, more potential donors enter the platform and they donate to all campaigns, including the less prominent ones. As a result, the less prominent campaigns also benefit from the market expansion effect of the exceptional performance of the prominent campaigns. These findings alleviate the concern that platforms' non-neutral practices, such as listing certain sellers more prominently than other sellers, could hurt the less prominent sellers, potential buyers, and ultimately, the platforms themselves.

The second essay examines how public statements from government officials affect private donations made to charitable crowdfunding campaigns. In particular, this essay examines how President Donald Trump's Twitter statements regarding the three major 2017 Atlantic hurricanes had a disproportionate effect on Hispanic fundraisers and donors on GoFundMe.

In this context, a clear pattern of ethnic homophily among Hispanic fundraisers and donors is observed, where Hispanic fundraisers receive a higher proportion of donations from Hispanic donors. The findings from this essay show that ethnic homophily among Hispanic donors and fundraisers is stronger following tweets from President Trump, even after controlling for official statements from government bodies and the corresponding media coverage. This increase is not entirely driven by negative statements, as a similar increase is observed even for positive and neutral tweets. It appears that the pre-existing negative view of President Trump plays a key role in shaping the pattern of private donations.

The contributions of the two essays in this dissertation go beyond the literature on crowdfunding. The findings from these two essays may also be of interest to platform designers, policymakers, and government officials as the findings help inform them of the potential effects of their actions on the digital economy. For instance, the findings from the first essay highlight the importance of a well-designed search function within a platform. The positive spill-over effect observed in this study hinges on potential buyers searching for sellers that best fit their preferences upon entering the platform, which would occur when their search costs are lower than the costs of a preference mismatch. If buyers simply transact with prominent sellers that are more visible without searching for other sellers that could match their preferences better, the positive spill-over effect may disappear altogether and the *Matthew effect* (i.e., the "rich get richer, the poor get poorer" condition highlighted in Merton (1968)) may be exacerbated. Therefore, to motivate buyers to search for sellers that best fit their preferences, platforms should design their search functions with the objective of reducing potential buyers’ search cost.

Another example is the contribution of the second essay to the growing body of literature on the effects of social media, particularly on the increasing use of social media by government officials, on society. The findings from the second essay suggest that the use of social media by government officials could have substantial and immediate effects on the dynamics of the interactions within and across ethnic groups even when the messages itself are not particularly inflammatory. As such, it may be optimal for public statements from government entities, for instance, information on disaster relief efforts, to be delivered through a more neutral channel to get the messages across and to avoid unintended consequences.

The rest of the dissertation is organized as follows. Chapters 2 and 3 discuss the two essays in detail. Chapter 4 concludes this dissertation with the limitations of the two essays and directions for future research.

Chapter 2 – How Do Non-Neutral Listing Practices on Digital Platforms Affect the Less Prominent Campaigns?

2.1. Introduction

Digital platforms have grown rapidly to be key players in the digital economy as they connect and enable trades between sellers and buyers (Kramer & Schnurr, 2018). These platforms are now the gatekeepers for access to content and trading online (European Commission, 2017; Kenney & Zysman, 2016; Morvan et al., 2016). With the increase of the reach and power of digital platforms in the fast-growing digital economy, many concerns have been raised about the practices utilized by these platforms that can have a significant effect on the welfare of sellers and buyers. A particularly important concern is regarding non-neutral practices on digital platforms, including the order in which sellers are listed on online platforms (e.g., European Commission, 2017; Kramer & Schnurr, 2018). Many sellers are concerned about their respective positions in the list displayed by the platform because it could have a significant impact on their sales as sellers who are listed on the top of the list (will be called *prominent sellers*, henceforth) are more likely to have better performance compared to the less prominent sellers (Animesh et al., 2011; Breugelmans, Campo, & Gijsbrechts, 2007; Jeziorski & Moorthy, 2018; Publications Office of the European Union, 2016).

The order in which sellers are listed is very important not only for sellers but also for buyers on online platforms. For instance, the practice of giving prominence to better sellers in the platform's listing, i.e., listing these sellers first in the platform's search list, may be useful for buyers in identifying good sellers. Displaying better sellers more prominently could help lower the search costs associated with identifying good sellers (Ursu, 2018). In the crowdfunding context, to the extent that each donor has a useful piece of information regarding a campaign's quality, the amount of donations that each campaign has received would be correlated with its quality (Belleflamme, Omrani, & Peitz, 2015; Zhang & Liu, 2012). A common listing practice among platforms that favors campaigns that have accumulated more donations would allow potential donors facing incomplete information regarding campaign quality to benefit from earlier donors' information.

However, buyers have diverse preferences. A display that gives prominence to certain campaigns could end up restricting a buyer's consideration set, potentially excluding non-prominent sellers who can match the buyer's distinct preference better. As a result, over time, the quality and variety of the product offerings on the platform may suffer as some sellers would not enter the market because the expected utility of non-prominent sellers may be negative (Kramer & Schnurr, 2018).

Examining non-neutral practices on digital platforms is difficult because researchers typically do not observe the counterfactuals: we only observe the outcome of what the platform does, but not the outcome of other practices or policies it could have chosen, including potentially more neutral practices. In this study, I take non-neutral practices on the platform as given and vary the attractiveness of campaigns that are listed more prominently on that platform. More specifically, I examine how the variation in the performance of these prominent campaigns affects the subsequent performance of the less prominent sellers within the same platform; i.e., whether the increase in performance of the prominent campaigns helps or hurts other campaigns. The results of the analyses shed some light on the debate of whether the non-neutral listing of sellers on a platform leads to an accumulated advantage outcome that is consistent with the Matthew effect (Merton, 1968).

The setting for this study is charitable campaigns on the largest charity-focused crowdfunding platform, GoFundMe. Crowdfunding platforms that connect fundraisers and donors have transformed charitable fundraising practices by allowing charitable fundraisers to solicit a large set of potential donors at a relatively low cost (Gomber et al., 2018). Therefore, it is not surprising that more and more charitable fundraisers, including those with limited experience, turn to crowdfunding platforms as a viable fundraising channel, resulting in many charitable campaigns sharing very similar causes and competing for contributions from a set of potential donors on the same platform. For instance, there are over 1,600 campaigns posted on GoFundMe in response to Hurricane Harvey, which hit the Texas Gulf Coast in August 2017.

GoFundMe does not offer fundraisers the opportunity to pay in order to be listed on the top of its search list, as one would typically find in search engine marketing (Animesh et al., 2011; Jeziorski & Moorthy, 2018; Narayanan & Kalyanam, 2015). However, when queried for a specific natural disaster event, the platform displays at most 500 campaigns related to that event in a certain order. While the algorithm used to select the listed campaigns as well as the order in which they are listed (will be called *ranking*, henceforth) is proprietary to GoFundMe, the ranking seems to be partially -- but not solely -- based on the amount of donations received, the number of donors contributing, and how active a campaign has been in attracting donation from donors thus far (see Table 2.2 for the characteristics of the campaigns in each ranking group). This indicates a listing order that is driven by demand and favors campaigns that have accumulated more donations.

Such listing order can also be seen on the landing page of other crowdfunding platforms, such as Indiegogo, Give.Asia, and Ketto. Indiegogo highlights its popular projects on its landing page, while Give.Asia and Ketto highlight their trending and successful campaigns on their respective landing pages. It is not surprising for two-sided markets like crowdfunding platforms to highlight campaigns that have attracted the most funding on their pages because such listing can help the platform to attract both fundraisers and funders. On one hand, highlighting campaigns that have received a great deal of supports from funders attracts fundraisers into a platform as it shows that there are plenty of available funders on the platform, increasing the probability of fundraisers in getting funding. On the other hand, highlighting campaigns have received a great deal of supports from other funders attracts funders into a platform as it shows that there are good quality campaigns on the platform, increasing the expected utilities that funders can receive from contributing (Armstrong, 2006; Belleflamme et al., 2015; Rochet & Tirole, 2003).

In this setting, do non-prominent campaigns operate at a disadvantage? In particular, I ask how a change in the performance of the prominent campaigns affects the non-prominent campaigns. On one hand, potential donors who come into a platform may not consider campaigns that are not readily visible to them and therefore would be more likely to donate to the prominent campaigns (Animesh et al., 2011; Kramer & Schnurr, 2018). Moreover, in the absence of fully revealing quality signal, as it is often the case in the crowdfunding setting, potential donors are likely to use the ability of the fundraisers on the platform in attracting funding thus far as a signal of quality (Zhang & Liu, 2012). Assuming that potential donors come into the platform without preference for a particular campaign and follow the decision of earlier donors, the more donors supporting the prominent campaigns, the less likely that potential donors would continue to search for alternative campaigns beyond those prominent ones. This could create a vicious cycle for the non-prominent campaigns.

On the other hand, prominent campaigns receive buzz on social media and even offline, increasing the exposure of the cause and the platform.[2] This will attract potential donors into the platform. When the prominent campaigns are performing exceptionally well, they are likely to receive more buzz as the donors who have contributed to those campaigns can act as advocates for the cause. Upon entering the platform, donors would then search for campaigns that best match their individual preferences to minimize the cost of preference mismatch (Hagiu, 2009; Lin, Wu, & Zhou, 2016). Indeed, they may then end up choosing non-prominent campaigns that match their preferences better than the prominent campaigns that initially attract them to the platform. Therefore, I expect that the total donor market for the cause and the platform would expand and that the expansion would benefit not only the prominent campaigns, but also the non-prominent campaigns due to the heterogeneity in donors' preferences.

The empirical findings in this study support the hypothesis that an increase in the performance of prominent campaigns results in positive externality for other campaigns sharing the same cause. Specifically, the empirical results show that the non-prominent campaigns also benefit when prominent campaigns perform exceptionally well. Donors coming into the platform seem to contribute to campaigns that best fit their preferences, increasing donations received by all

[2] Table 2.2 shows that the first 45 campaigns listed on GoFundMe search list for a particular disaster event are mentioned on social media more than the less prominent campaigns on the list.

campaigns, not just the prominent campaigns. To the extent that the platform receives a proportionate share of the total donation received by campaigns it hosts, it also benefits from the exceptional performance of prominent campaigns.

These findings help to mitigate the concern that non-neutral practices can hurt non-prominent sellers as well as buyers on the platform. Sellers should still enter the market, even when they are not prominently listed, because they would not operate at a disadvantage. This should alleviate the concern that the product offerings on the platform may deteriorate over time as a result of the non-neutral practices of the platform.

The rest of Chapter 2 is organized as follows. The next section provides the theoretical background for the hypothesis tested in this study. The dataset and empirical setting are then discussed, followed by the results from the empirical analyses. Chapter 2 is concluded with a summary of the findings and their implications for research and practice.

2.2. Hypotheses development

Andreoni (1990) and Ribar & Wilhelm (2002) posit that donors receive positive utilities from contributing to charities in the forms of the joy of improving the well-being of the beneficiaries (altruism) and the joy of making a donation (joy-of-giving or warm glow). However, donors' positive utility from giving is offset by the cost of mismatched preference when the charities they support do not perfectly match their preferences (Lin et al., 2016). Consistent with the utility functions posited by Lin et al. (2016) and Ribar & Wilhelm (2002), I propose the following donor's utility function (Equation 2.1).

$$Donor_{ij} = h_{ij} + H_j - td_{ij} \qquad \text{s.t. donor } i\text{'s budget constraint} \qquad (2.1)$$

The term h_{ij} is the positive utility received by donor i from making a donation regardless of donor i's selection of charity (i.e., joy-of-giving). This term represents the amount of donation given by donor i (Andreoni, 1990; Ribar & Wilhelm, 2002). H_j is the positive utility received by altruistic donor i from helping the intended beneficiaries. This term is the sum of all donations received by charity j (i.e., the sum of all h received by charity j) and it represents the output of charity j because charity j acts as an intermediary that delivers the output of the project financed by all the donations it receives to the intended end beneficiaries. In the context of this study, fundraiser and charity are conceptually equivalent as most fundraisers on charitable crowdfunding platforms have only one project and only one fundraiser is listed for each project. The sum of the two terms, h_{ij} and H_j, describes the total utility donor i receives from giving to fundraiser j's project when the project is the ideal match to donor i's preference. The term d_{ij} should be interpreted as the degree of mismatch between donor i's preference and fundraiser j's project, and t as the unit cost associated with the mismatched preference (Lin et al., 2016).

To maximize their utilities, donors would donate to high quality projects (i.e., maximizing H_j) that closely match their preferences (i.e., minimizing td_{ij}). Donors' ability to maximize their utility from the joy-of-giving (h_i) is limited by their giving levels relative to their means. Prior to entering a platform, potential donors do not know whether their preferences can be matched by the projects that are available on the platform. Facing such uncertainty, potential donors are more likely to enter a platform with higher expected project quality in order to offset the potential costs of preference mismatched.

In the crowdfunding setting, information regarding the quality of a project is often incomplete (Agrawal, Catalini, & Goldfarb, 2014; Mollick, 2014). In the absence of fully revealing quality signal, potential donors often rely on the decision of earlier donors when choosing a charity to support, making the campaign's success in attracting donors thus far as a signal of its quality (Belleflamme et al., 2015; Zhang & Liu, 2012). The effect of this quality signal is amplified when the campaign is highly visible. Therefore, when highly visible campaigns on a particular platform perform exceptionally well, this can generate a good quality signal for the platform as a whole through social media and offline buzz, increasing donors' expected utility. As such, I expect more donors to enter the platform when the most visible campaigns perform well.

The main research question is whether the increase in the performance of the prominent campaigns attracts additional donors into the platform. If it does, do these donors donate to non-prominent campaigns? One may expect that donors only contribute to campaigns that are the most visible to them. However, once they enter the platform, potential donors may search for campaign characteristics that best fit their preferences to minimize the cost of preference mismatch (Hagiu, 2009; Lin et al., 2016). As donor's preferences are likely to be heterogeneous, even the non-prominent campaigns would benefit from the additional donors coming into the platform because the non-prominent campaigns may fit the preferences of some donors better than the prominent campaigns.

In this study, GoFundMe's proprietary ranking is used to directly capture the prominence of each campaign. The platform displays at most 500 campaigns on its search list for a particular disaster event, with each page displaying nine campaigns. This study considers the first 5 pages on the list for a particular event as prominent campaigns because they are more visible to potential donors on the platform. Given the lack of convention of which positions on a search list should be considered as prominent, I choose a reasonable cutoff of the first 5 pages. As each page contains 9 campaigns, the first five pages contain 45 campaigns, which are approximately the first one-tenth of the 500 campaigns on the list.[3]

In this study, I focus on the market share of the prominent campaigns to measure the performance of those campaigns, i.e., the proportion of total donations that are associated with the first 45 campaigns on the list of campaigns supporting the same cause (Jacobson, 1988).[4] More precisely, *EarnRatio_45* is defined as the portion of the donations received by the first 45 campaigns over the donations received by all campaigns sharing the same cause (Equation 2.2). The ratio captures the performance of the prominent campaigns relative to other campaigns sharing the same cause. The relative performance of the prominent campaigns is useful to control for the day-to-day variations of the performance of campaigns on the platform that are driven by other factors that are difficult to capture using dataset (e.g., the variation in platform's marketing efforts).

$$EarnRatio\_45_{t,e} = \frac{Total\ donations\ received\ by\ first\ 45\ campaigns_{t,e}}{Total\ donations\ received\ by\ all\ campaigns_{t,e}} \quad (2.2)$$

[3] The *three-click rule* is a commonly used rule-of-thumb in website design. It states that users should be able to find the information they need within 3 clicks (Three-click rule, n.d.). If this study was to follow this rule, then the first 3 pages could be considered as prominent positions (i.e., 1 click to get to the platform and 2 additional clicks to get to pages 2 and 3). However, this rule has been challenged by researchers in the field of user experience who have documented that users do not stop at 3 clicks (e.g., Laubheimer, 2019; Porter, 2003). As such, I use 5 pages for the baseline analysis but also report additional cutoffs in Section 2.6.1.

[4] Campaigns sharing the same cause is defined as campaigns that support the relief efforts associated with a particular natural disaster event.

t is defined as the daily time index and *e* is defined as the index for each natural disaster event in the dataset. Therefore, I hypothesize the following:

> **Hypothesis 2.1 (the effect of a change in the performance of the prominent campaigns):**
>
> *An increase in EarnRatio_45 leads to an increase in the amount of donations received by the non-prominent campaigns.*

2.3. Data description

This study utilizes a panel dataset containing charitable campaigns raising money to support disaster relief efforts on GoFundMe. Publicly available data were collected daily from GoFundMe's website, www.gofundme.com, in 2016 and 2017. The length of the daily data collection is at least 50 days following the occurrence of each disaster event. The panel dataset contains daily data of 5,418 charitable campaigns supporting the relief efforts associated with five major natural disaster events: Hurricane Matthew (September 2016), Hurricane Harvey (August 2017), Hurricane Irma (September 2017), Hurricane Maria (September 2017), and Mexico City earthquake (September 2017). This study focuses on campaigns aiming to support major natural disaster relief efforts to mitigate the (potentially large) variation in the perceived worthiness of causes.[5]

GoFundMe is a charity-focused crowdfunding platform. It is the first-ranked charity-focused crowdfunding platform based on site traffic as recorded by Alexa.com (Mercer, 2016). It trails only Kickstarter, Indiegogo, and Patreon, which

[5] Campaigns on charitable crowdfunding platforms support a variety of causes. Some campaigns even support causes that are not typically associated with charities, such as raising funds for a vacation. An example of such campaign is https://www.gofundme.com/AmieeVacationFunds

are not charity-focused crowdfunding platforms. Fundraisers on GoFundMe have raised more than US$ 3 billion in total since the platform's inception in 2010 (Adams, 2016).

The charitable crowdfunding campaigns in the dataset raised a total of US$ 32.6 million from over 300,000 donors by the end of the data collection periods (see Table 2.1). While campaigns on GoFundMe can stay open for a long time even after their funding goals are reached, the 50-day observation window is sufficient to capture the campaigns' life cycle. As shown in Figure 2.1, these campaigns do not receive much donations beyond 30 days after the occurrence of the events they are associated with. The relatively short active period of fundraising is consistent with the urgent nature of natural disaster relief efforts and the short attention span given by media to such events. However, there are still some variations left in the amount of donation received by each campaign beyond the first 30 days.

Table 2.1. Summary of dataset, by event

Event	Date	Number of Campaigns	Total Donations	Total Donors
Hurricane Matthew	Oct 2016	827	$2,887,946	29,957
Hurricane Harvey	Aug 2017	1,635	$17,295,794	153,637
Hurricane Irma	Sept 2017	1,465	$6,283,220	55,640
Hurricane Maria	Sept 2017	1,364	$5,888,798	58,807
Mexico City earthquake	Sept 2017	127	$221,148	2,181
Total		5,418	$32,576,905	300,222

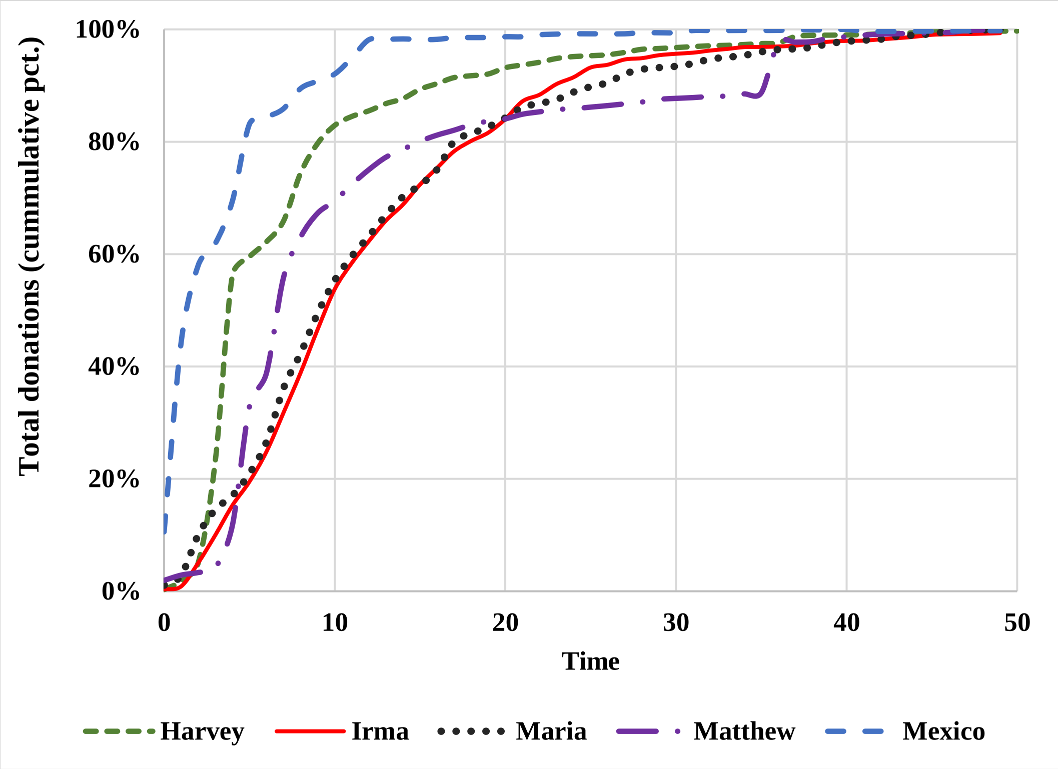

Figure 2.1. Total donations received (cumulative), by event daily

When queried for a specific natural disaster event, GoFundMe displays at most 500 campaigns related to that event. For the analyses, I focus on campaigns that appear on the list displayed by GoFundMe on a particular day, *t*. This approach allows me to measure the amount of donation received on day *t*+1 as the difference between the total donation amount in day *t*+1 and the total donation amount in day *t*. Therefore, the analysis in this study employs at most 500 campaigns during each day following a particular natural disaster.

All campaigns that have appeared on GoFundMe's list thus far are used to calculate the independent variable of interest: the ratio of donations received by prominent vs. all other campaigns supporting the same cause. Similarly, all campaigns that have appeared on GoFundMe's list supporting the same cause are used to calculate the number of campaigns. This is done because donors can still access every active campaign, including those not appearing on GoFundMe's list, using a direct link to the campaign's page. The number of campaigns supporting the same cause is used to control for the negative effect of competition among these campaigns.

This study measures each campaign's prominence using the platform's proprietary ranking, i.e., the order in which campaigns appear on GoFundMe's list. GoFundMe employs a proprietary algorithm to select the campaigns that appear when donors search for campaigns associated with a particular disaster event and the order in which these campaigns are listed.[6] However, it appears that GoFundMe's algorithm seems to follow the recency, frequency, and monetary (RFM) methodology commonly used in marketing to identify the most valuable customers (Fader, Hardie, & Lee, 2005).[7] Consistent with the RFM methodology, GoFundMe appears to rank relevant campaigns sharing the same cause based on the recency of their last activities, the amount of donations received, and the number of donors contributing to the campaigns. Table 2.2 summarizes the characteristics of the campaigns in each ranking group. In this study, the prominence of each campaign is measured daily. It appears that GoFundMe's list of campaigns and the order in which campaigns supporting similar causes are listed are fairly stable across consecutive days (Table 2.3).

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[6] This study utilizes the list of campaigns that are displayed by GoFundMe when a particular disaster event is used as keywords in the platform's search function. The resulting list displays at most 500 campaigns that are relevant to the given keywords.

[7] Recency, monetary, and frequency methodology (RFM) is often used in marketing to determine the value of a customer. The value of a customer for a firm is determined by her/his past behavior in terms of her/his most recent purchase (recency), the average amount spent (monetary), and the number of past purchases (frequency) (Fader et al., 2005).

Table 2.2. Campaign characteristics by ranking group

		Ranking				
		0-44	45-89	90-134	135-179	Above 180
Average/campaign	Total donations	$27,915	$11,354	$8,239	$5,056	$2,642
	Number of donors	264	99	70	49	25
	Total active days*	8.3	6.1	5.3	5.8	3.5
	Total mentions on social media	1,110	436	297	236	118
	Number of fundraiser's FB friends	787	728	683	670	672
	Length of project description (words)	267	240	240	226	197
	Funding goal	$78,048	$24,695	$22,788	$24,440	$97,963
% of female fundraisers		49%	51%	49%	52%	51%
% of fundraisers from affected areas		34%	33%	38%	34%	40%

Note: *Total active days is defined as the number of days campaign *i* receives donations from donors (i.e., the number of days the amount of donations received that day is not zero).

Table 2.3. Percentage of campaigns in each ranking group

	Ranking	Time = t				
		0-44	45-89	90-134	135-179	Above 180
Time=t-1	0-44	**88.0%**	7.6%	1.7%	1.2%	1.6%
	45-89	7.5%	**76.9%**	7.2%	2.4%	6.1%
	90-134	1.0%	11.9%	**70.6%**	7.0%	9.5%
	135-179	0.6%	2.0%	13.8%	**64.7%**	18.9%
	Above 180	0.1%	0.4%	1.1%	3.5%	**94.9%**

2.4. Empirical model

The empirical model in Equation 2.3 is used to test the effect of increased performance of the prominent campaigns on other campaigns supporting the same cause. The dependent variable in the empirical model is the amount of donations (in US Dollars) received by campaign *i* at time *t*+1 (*Donations*). The dependent variable is logarithmically transformed to reduce the skewness of the variable. In the analyses, the amount of donation received is separated by the prominence of the campaign on the platform to examine how the effect of increased performance of the prominent campaigns differs for campaigns with less prominence.

$$\ln{(Donations)}_{t+1,i} = \alpha_1 * EarnRatio\_rk45_t + \mathrm{B} * X + \Theta * Z + \varepsilon \qquad (2.3)$$

The independent variable of interest is $EarnRatio\_45$, which is defined as the ratio of the total donations received by the first 45 campaigns on the list of those supporting the relief efforts of the same disaster event as campaign *i* over the total donations received by all campaigns sharing the same cause at time *t* (see Equation 2.2).

Two sets of control variables are included to mitigate potential endogeneity concerns. First, to capture time-invariant heterogeneity across campaigns, campaign fixed effects (*Z*) are included in the model. It is crucial to include campaign fixed effects as the success of each campaign can depend on its own characteristics as well as the characteristics of the disaster event it is associated with. Second, a vector of control variables is included in the empirical model (*X*) to mitigate potential omitted variable concerns. These control variables include (1) the number of campaigns supporting the relief efforts of the same event as campaign *i* *(NumCampaigns)*, (2) the percentage of first 45 campaigns that have raised at least 100% of their respective funding goals (*Metgoal_45*), (3) the number of published news articles on the disaster event associated with campaign *i* (*NewsCntr*), (4) the number of times campaign *i* is shared on social media (*SocialMedia*), (5) the number of updates posted by fundraiser *i* (*Updates*), and (6) a binary indicator for the first five days since the occurrence of another natural disaster event (*NewEvent*).

The number of campaigns sharing the same cause is included to capture the negative effect of competition among campaigns. Existing literature have documented that similar firms in the market steal business from one another (Aldashev & Verdier, 2010; Ly & Mason, 2012; Mankiw & Whinston, 1986). Such negative effect has also been documented in the context of two-sided markets (Hagiu, 2009; Lin, et al., 2016). As such, I expect campaigns to steal donors from one another because donors are unlikely to donate to all campaigns providing them with positive utility due to their budget constraints.

The percentage of the first 45 campaigns that have raised at least 100% of their respective funding goals (*Metgoal_45*) is used to capture the *crowding-out* effect that could potentially drive the results. Crowding out effect has been documented in existing studies on crowdfunding and traditional charitable giving (Abrams & Schitz, 1978; Andreoni & Payne, 2003; Andreoni & Payne, 2011; Burtch, Ghose, & Wattal, 2013; Payne, 1998; Ribar & Wilhelm, 2002; Roberts, 1984). This effect occurs when donors reduce their donations to a charity after they observe that other donors or the government contribute to the same causes supported by the charity. In such cases, donors reduce their donation because they view their contributions to the cause as less essential. In the context of this study, crowding out occurs when donors reduce their contributions to the prominent campaigns that have met their funding goals because donors view their donations as less essential in helping the fundraisers fulfil their funding goals (Burtch et al., 2013). Donors may shift their donations to the less prominent campaigns when the prominent campaigns meet or exceed their respective funding goals, leading to a positive externality for the non-prominent campaigns. *MetGoal_45* is defined as a portion of the first 45 campaigns that have met or exceeded their funding goals (see

Equation 2.4). On average, 24% of the top 45 campaigns have reached their respective funding goals (see Table 2.4).

$$MetGoal\_45_{t,e} = \frac{Number\ of\ first\ 45\ campaigns\ exceededing\ their\ goal_{t,e}}{Number\ of\ first\ 45\ campaigns_{t,e}} \tag{2.4}$$

t is the daily time index and *e* is the index for each natural disaster event in the dataset.

The number of published news articles on each disaster event associated with campaign *i* (*NewsCntr*) on day *t* is included to capture the time-series variation in the popularity of each event. The daily count is obtained from Factiva and only includes published articles in English and does not include blogs. It is important to capture the relative popularity of the event in the model to avoid potential endogeneity issues caused by omitted variable bias. The inclusion of the news articles count in the model can alleviate the concern regarding the potential effects of the relative attention received by a particular event on the amount of donations given to campaigns associated with that event. The variable *NewsCntr* is centered on its mean because zero news articles are meaningless in this case.

The number of times campaign *i* is shared on social media (Facebook and Twitter) can affect the amount of donations received by campaign *i* as social media mentions can serve as endorsements for campaign *i*. The number of updates posted by fundraiser *i* can also affect the amount of donations received by campaign *i* as it represents a more active fundraiser (Mollick, 2014). The *NewEvent* binary indicator variable is included in the model to control for the effect of another natural disaster event occurring during the 50-days fundraising period captured in the dataset. In particular, the *NewEvent* variable captures the potential effect of the occurrence of a new disaster event that attracts public interests and can detract potential donors' attention from the focal event. Table 2.4 displays the summary statistics of the variables included in the model. The independent variables are measured by the beginning of day *t* (i.e., before the dependent variable is measured).

Table 2.4. Variables summary statistics

Variable	Mean	Std. dev
Donations (USD)	$135.21	$1,658.21
Donors	1.21	18.89
Earn ratio of first 45 campaigns	0.25	0.15
Percentage of first 45 that have met/exceeded their funding goals	0.24	0.14
Number of campaigns	1952.81	745.46
Number of news articles	30.84	497.51
Social media mentions	5.14	74.56
Number of updates	0.04	0.27

The empirical model in Equation 2.3 is estimated using a panel regression method with campaign fixed effects. Time period clustering is also used in the regression to control for within-time-period. The correlation matrix and variance inflation factor (VIF) of the dependent variables are included in Appendix A. They indicate that multicollinearity is not a concern in this study.

2.5. Empirical results

The parameter estimates of the panel regression are reported in Table 2.5. The positive estimate for *EarnRatio_45* in column 1 indicates that the relative success of the prominent campaigns (i.e., the first 45 campaigns) expands the market in the form of more donations made to campaigns sharing the same cause as the prominent campaigns. This supports the hypothesis that an increase in the performance of the prominent campaigns brings more donors into the platform.[8]

The results in columns 2 to 5 of Table 2.5 show that non-prominent campaigns – including those listed beyond the first 20 pages of the search results – receive more donations when the prominent campaigns perform exceptionally well.[9] These findings suggest that an increase in the performance of the prominent campaigns has a positive spill-over effect on non-prominent campaigns.

Table 2.5. The effect of a change in the performance of the prominent campaigns

	ln(*Donations*)				
	(1)	(2)	(3)	(4)	(5)
	All campaigns	Non-prominent campaigns			
VARIABLES		45-89	90-134	135-179	Above 180
EarnRatio_45	4.913***	0.928*	6.276***	8.765***	3.683**
	(0.6570)	(0.5271)	(1.3451)	(2.8701)	(1.5244)
NumCampaigns	-0.011***	-0.020***	-0.015***	-0.011***	-0.010***
	(0.0013)	(0.0028)	(0.0028)	(0.0028)	(0.0022)
Metgoal_45	-1.345	0.147	2.478	-1.524	-2.986**
	(1.2185)	(2.0251)	(1.8513)	(1.6818)	(1.1728)
NewEvent	0.198	0.502	0.041	0.769	0.058
	(0.2552)	(0.3944)	(0.3480)	(0.4845)	(0.2470)
NewsCntr	0.001***	0.002**	0.001	0.000	0.001***
	(0.0004)	(0.0008)	(0.0006)	(0.0006)	(0.0004)
SocMedia	0.002***	0.005*	0.008**	0.076***	0.035***
	(0.0004)	(0.0029)	(0.0033)	(0.0143)	(0.0068)
Updates	1.108***	0.850**	0.682**	1.128***	0.585***
	(0.0768)	(0.3495)	(0.2897)	(0.3375)	(0.1145)
Intercept	15.372***	28.914***	21.235***	15.865***	15.647***
	(2.6731)	(4.7840)	(5.3515)	(5.9264)	(4.9343)
Observations	74,170	7,114	6,936	6,104	39,036
R-squared	0.459	0.686	0.692	0.677	0.438

[8] The results in Table 2.7 show that more donors contribute to non-prominent campaigns when prominent campaigns perform well. Moreover, Table 2.10 shows that the number of new donors increases when the prominent campaigns perform well.

[9] The subsequent performance of the prominent campaigns is also positively correlated with *EarnRatio_45* as reported in Table B.1. in Appendix B. However, it is difficult to infer causality on the effects of an increase in the relative performance of the prominent campaigns on their own subsequent performance, as this may be due to heterogeneity across campaigns, e.g., good campaigns receive more donations day after day. This concern would not afflict the main analyses, in which the focus of the analyses is on a different subset of campaigns.

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

Table 2.5 also shows that the effect is relatively weaker for non-prominent campaigns that fall right below the prominent campaigns (i.e., ranked 45 to 89, see column 2). There are two potential related reasons for this. First, this group of campaigns is likely to share similar characteristics to those ranked immediately above them, resulting in both sets of campaigns being ranked highly by GoFundMe's proprietary algorithm. Given this potential similarity, donors whose preferences match the first set of campaigns are likely to choose those campaigns given their higher visibility on GoFundMe and potentially higher quality (as evidenced by their higher ranking). This is related to the concern of "the rich get richer". Second, donors whose preferences do not match both sets of campaigns at the top of the list are more likely to be attracted by campaigns that are ranked lower by GoFundMe's proprietary algorithm, which are likely to have different objectives from those ranked higher by the algorithm. Nevertheless, we observe a positive externality even for this group of less-prominent campaigns.

Given the positive externality observed across all campaigns in all ranking groups, it is obvious that the platform as a whole benefits from the exceptional performance of the prominent campaigns as the amount of donations raised by the campaigns on the platform directly affect the platform's revenue.[10] Table 2.6 shows the regression estimates using the aggregated donations at the platform level. In this case, the dependent variable is the total donations raised by all campaigns

[10] Similar to many other crowdfunding platforms, during the data collection period, GoFundMe collected a portion of the donations received by each campaign as a fee. GoFundMe has stopped charging platform fee since 2018 (https://www.gofundme.com/c/blog/gofundme-fees).

supporting a particular disaster event each day and the empirical model in Equation 2.3 is estimated using event-day as the observation unit.

The positive estimate for *EarnRatio_45* in Table 2.6 indicates that the increase in the performance of the prominent campaigns leads to more donations at the platform level. This suggests that the superior performance of the prominent campaigns benefits the platform as a whole as the platform's revenue is related to the amount of donations received by the campaigns on it. The platform as a whole also benefits from an increase in the number of campaigns (see the positive estimate of *NumCampaigns* in Table 2.6). However, this increase in the number of campaigns brings negative effect for each campaign sharing the same cause on the platform (see the negative estimate for *NumCampaigns* in Table 2.5). An increase in the number of campaigns leads to lower donations received by every campaign. This result is expected as the business stealing effect is likely to intensify as more campaigns sharing the same cause compete in the market.

It is also worth noting that the crowding-out effect occurs as expected. The negative estimate for *Metgoal_45* in Table 2.6 suggests that the amount of donation decreases as more campaigns fulfil their respective funding goal. The arrival of a new disaster event, however, appears to increase the total donations for a particular event. This is likely because the campaigns in the dataset share the same focus (i.e., supporting the relief efforts for disaster events) and the arrival of a new disaster event may renew the public's interest in donating to such causes.

Table 2.6. The effects of a change in the performance of the prominent campaigns on total donations raised on the platform

VARIABLES	ln(*Total Donations*)
EarnRatio_45	8.184***
	(1.3336)
NumCampaigns	0.003*
	(0.0015)
Metgoal_45	-7.055**
	(3.3278)
NewEvent	1.524**
	(0.6846)
NewsCntr	0.001
	(0.0007)
Intercept	3.368
	(2.4809)
Observations	237
R-squared	0.571

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Event fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.6. Additional results

2.6.1. Alternative definition of prominent campaigns

To test for the sensitivity of the main empirical results above, I vary the cut-off that is used to categorize prominent campaigns. I perform the sensitivity analyses by changing the definition of prominent campaigns as those listed on the first page, the first 2 pages, the first 3 pages, or the first 4 pages. The results of the additional regressions are displayed in columns 1 to 4 of Table 2.7. The result from the main regression is included in column 5 for comparison.

The results reported in Table 2.7 suggest that the positive spill-over effect enjoyed by the non-prominent campaigns remains robust with a more restrictive definition of prominence (columns 2 to 4), except for when only the top 9 campaigns are considered as prominent campaigns (column 1). There are two potential explanations as to why the estimate for *EarnRatio_9* is not statistically significant. First, there may not be enough variation in *EarnRatio_9*. The standard deviation of *EarnRatio_9* is lower than the standard deviation of the main variable of interest, *EarnRatio_45* (0.10 versus 0.15, respectively). Second, the top 9 campaigns may not get enough buzz online and/or offline to generate the market expansion effects that could benefit non-prominent campaigns.

Table 2.7 The effect of a change in the performance of prominent campaigns with varying definitions of prominence

	ln(*Donations*)				
	(1)	(2)	(3)	(4)	(5)
	Non-prominent campaigns				
VARIABLES	Ranked >9	Ranked >18	Ranked >27	Ranked >36	Ranked >45
EarnRatio_45					4.325***
					(0.8152)
EarnRatio_9	0.936				
	(1.0401)				
EarnRatio_18		2.506***			
		(0.8042)			
EarnRatio_27			3.403***		
			(0.7172)		
EarnRatio_36				4.180***	
				(0.6867)	
NumCampaigns	-0.013***	-0.012***	-0.012***	-0.012***	-0.011***
	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0015)
MetGoal_45	-1.023**	-2.817***	-3.046***	-3.106***	-0.646
	(0.4238)	(0.7084)	(0.6995)	(0.6877)	(1.1577)
NewEvent	0.344	0.249	0.190	0.126	0.135
	(0.2428)	(0.2206)	(0.2205)	(0.2189)	(0.2474)
NewsCntr	0.001***	0.001***	0.001***	0.001**	0.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
SocMedia	0.004***	0.007**	0.007**	0.008**	0.009***
	(0.0011)	(0.0028)	(0.0030)	(0.0031)	(0.0033)
Updates	1.123***	1.078***	1.033***	1.019***	1.002***
	(0.0973)	(0.1028)	(0.1035)	(0.0965)	(0.0926)
Intercept	21.214***	19.505***	18.597***	17.494***	16.449***
	(2.9536)	(2.8334)	(2.7599)	(2.8498)	(3.0997)
Observations	72,551	70,934	69,315	67,691	66,052
R-squared	0.434	0.424	0.417	0.411	0.402

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.6.2. The effects on the number of donors

Table 2.8 shows the regression estimates for an alternative specification of the dependent variable in the empirical model in Equation 2.3. The dependent variable in the empirical model is changed to the number of donors contributing to campaign *i* (*Donors*) to examine the effect of the change in the performance of the prominent campaigns on the number of donors. The positive externality observed previously remains robust in this modified model. Specifically, an increase in the performance of the prominent campaigns leads to more donors contributing to non-prominent campaigns sharing the same cause, suggesting that the exceptional performance of the prominent campaigns expands the market in the form of both more donors and higher donations.

Table 2.8. The effects of a change in the performance of the prominent campaigns on the number of donors

	ln(*Donors*)				
	(1)	(2)	(3)	(4)	(5)
	All campaigns	Non-prominent campaigns			
VARIABLES		45-89	90-134	135-179	Above 180
EarnRatio_45	3.191***	0.587*	4.122***	5.660***	2.408**
	(0.4325)	(0.3385)	(0.8863)	(1.8457)	(0.9836)
NumCampaigns	-0.007***	-0.013***	-0.010***	-0.007***	-0.007***
	(0.0009)	(0.0019)	(0.0019)	(0.0018)	(0.0014)
Top45goalmet_ratio	-0.871	0.369	1.675	-0.932	-1.904**
	(0.7912)	(1.3057)	(1.2002)	(1.0847)	(0.7562)
NewEvent	0.110	0.312	0.009	0.461	0.016
	(0.1663)	(0.2609)	(0.2278)	(0.3054)	(0.1580)
NewsCntr	0.001***	0.001**	0.000	0.000	0.001**
	(0.0003)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
SocMedia	0.001***	0.004*	0.006**	0.050***	0.023***
	(0.0003)	(0.0020)	(0.0022)	(0.0091)	(0.0045)

Updates	0.737***	0.594**	0.433**	0.735***	0.383***
	(0.0508)	(0.2331)	(0.1864)	(0.2261)	(0.0718)
Intercept	8.039***	16.939***	11.965***	7.907**	7.805**
	(1.7359)	(3.2098)	(3.6666)	(3.8709)	(3.1654)
Observations	74,183	7,115	6,937	6,104	39,040
R-squared	0.473	0.698	0.701	0.682	0.442

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.6.3. The effects on the campaigns at the bottom of search list

Table 2.9 shows the effects of the change in the performance of the prominent campaigns on the 50 campaigns that appear at the very end of the list. These campaigns are the least visible because the platform does not allow donors to easily jump directly to the end of the list. On GoFundMe, donors have to click "Show More" multiple times to arrive at these campaigns, unless they use a direct link or search specifically for these campaigns. The results show that even campaigns that are ranked last in the list benefit from a relative increase in the performance of the prominent campaigns.

Table 2.9. The effects of a change in the performance of the prominent campaigns on the bottom 50 campaigns

	Bottom 50 campaigns	
	(1)	(2)
VARIABLES	ln(*Donations*)	ln(*Donors*)
EarnRatio_45	3.981***	2.369**
	(1.3662)	(1.0062)
NumCampaigns	-0.082	-0.063
	(0.0691)	(0.0492)
Metgoal_45	7.410*	4.573*
	(3.9815)	(2.6655)
NewEvent	-3.010***	-1.994***
	(0.6908)	(0.4743)
NewsCntr	0.005	0.003
	(0.0074)	(0.0051)
SocMedia	0.055***	0.036***
	(0.0175)	(0.0114)

Updates	-0.472	-0.307
	(0.4347)	(0.2747)
Intercept	2.358	0.375
	(9.4235)	(6.7369)
Observations	1,163	1,163
R-squared	0.348	0.348

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.6.4. The effects of a change in the absolute performance of the prominent campaigns

While the relative measure of the performance of the prominent campaigns (*EarnRatio_45*) is useful to control for the ups and downs of the performance of all the campaigns on the platform due to other factors, the change in the relative performance can be driven by the change in the performance of the non-prominent campaigns instead of the change of the prominent campaigns. To test for the robustness of the findings in this study, *EarnRatio_45* in Equation 2.3 is replaced by the absolute measure of the performance of the prominent campaigns (ln(*Donation_45*)). *Donation_45* is defined as the total amount of donations received by the first 45 campaigns on the platform's search list on day *t*, indicating the absolute performance of the prominent campaigns.

Table 2.10 shows the effect of the change in the absolute performance of the prominent campaigns. The positive externality previously observed remains robust when the performance of the prominent campaigns is measured in an absolute term.

Table 2.10. The effect of a change in the absolute performance of the prominent campaigns

	ln(*Donations*)				
	(1)	(2)	(3)	(4)	(5)
	All campaigns	Non-prominent campaigns			
VARIABLES		45-89	90-134	135-179	Above 180
ln(*Donation_45*)	0.934***	0.663*	1.914***	1.712***	0.506*
	(0.2466)	(0.3767)	(0.4306)	(0.5180)	(0.2929)
NumCampaigns	-0.015***	-0.021***	-0.021***	-0.019***	-0.013***
	(0.0015)	(0.0029)	(0.0028)	(0.0034)	(0.0017)
MetGoal_45	-0.610	0.212	3.001	-0.705	-2.534**
	(1.2010)	(1.9956)	(1.8454)	(1.5665)	(1.1590)
NewEvent	0.142	0.450	-0.049	0.652	0.041
	(0.2441)	(0.4010)	(0.3448)	(0.4638)	(0.2447)
NewsCntr	0.001***	0.002**	0.001	0.001	0.001***
	(0.0004)	(0.0008)	(0.0006)	(0.0006)	(0.0004)
SocMedia	0.002***	0.005*	0.008**	0.078***	0.035***
	(0.0004)	(0.0029)	(0.0032)	(0.0144)	(0.0074)
Updates	1.148***	0.852**	0.694**	1.146***	0.595***
	(0.0819)	(0.3472)	(0.2760)	(0.3316)	(0.1170)
Intercept	12.123***	22.773***	8.327	9.685	15.820***
	(3.4460)	(6.3338)	(7.0016)	(7.9063)	(5.7543)
Observations	74,170	7,114	6,936	6,104	39,036
R-squared	0.456	0.687	0.692	0.676	0.438

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.6.5. The effects on new donors on the platform

The findings presented in the preceding sections of this study suggest that non-prominent campaigns enjoy positive benefit in the form of more donors and higher amount of donations when the prominent campaigns perform well. However, these findings may not necessarily show that the market expands as a result of the increase in the performance of the prominent campaigns because these donors may be existing donors who repeat their contributions. In order to examine whether the donors market expands, the outcome variable in Equation 2.3 need to be restricted to include only first-time donors. To do so requires a dataset that contains donors’ information that can be utilized to reliably identify unique donors, such as a unique identification number for each donor.

The dataset utilized in this study does not contain such donors' information. In fact, only campaigns associated with three out of the five disaster events in the dataset contain identifiable donors' information.[11] This subset dataset accounts for 82.4% of the total number of campaigns in the full dataset (4,464 campaigns), raising 90.5% of the total amount of donation from 89.3% of total donors in the full dataset (US$29.5 million from over 268,000 donors). Of the donors in the subset dataset, 90.0% of them (241,288 donors) provided their names that can be utilized to identify them (they will be referred to as *non-anonymous donors*, henceforth). Donations from the non-anonymous donors accounted for 87.0% of the total donations received by the campaigns in the subset dataset (US$ 25.6 million).

Due to the data limitation, first-time donors can only be identified using their first and last names. Using this identification method, 91.8% of non-anonymous donors are identified as first-time donors (221,582 donors) and the rest are repeat donors. It is important to note that less than 1% of the non-anonymous donors contribute more than twice. Assuming that the other two events in the full dataset contain a similar proportion of first-time donors, the findings presented in the preceding sections show donors market expansion as a result of an increase in performance of the prominent campaigns.

Nevertheless, additional regressions were performed using the subset dataset containing only first-time donors and the results are presented in columns 1 and 2 of Table 2.11. The results of the regressions using the subset dataset without first-

[11] Only campaigns associated with the 2017 hurricanes (i.e., Harvey, Irma, and Maria) contain identifiable donors' information in the form of first and last names.

time donors identification (columns 3 and 4) and the results of the regressions using the full dataset (columns 5 and 6) are included for comparison. The results in columns 1 and 2 are directionally similar to the results in columns 3 to 6. They suggest that donors market indeed expands (i.e., more donors give) when the prominent campaigns perform well and that this market expansion benefits not only the prominent campaigns, but also the non-prominent campaigns sharing the same cause.

Table 2.11 The effects on new donors

	ln(*Donors*)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Subset dataset - 1st time donors		Subset dataset - all donors		Full dataset	
VARIABLES	Prominent campaigns	Non-prominent campaigns	Prominent campaigns	Non-prominent campaigns	Prominent campaigns	Non-prominent campaigns
EarnRatio_45	7.933***	2.086***	7.677***	2.698***	4.277***	2.803***
	(1.2354)	(0.7816)	(1.1970)	(0.7877)	(0.5154)	(0.5319)
NumCampaigns	-0.006***	-0.007***	-0.005***	-0.008***	-0.006***	-0.008***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
MetGoal_45	-1.306	0.033	-1.793	-0.022	-2.749*	-0.371
	(1.6018)	(0.7112)	(1.5431)	(0.8213)	(1.5670)	(0.7481)
NewEvent	0.700**	0.057	0.596**	0.099	0.511**	0.071
	(0.2950)	(0.1410)	(0.2740)	(0.1649)	(0.2482)	(0.1601)
NewsCntr	0.001***	0.001**	0.001***	0.001**	0.001***	0.001**
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
SocMedia	0.000**	0.005***	0.000**	0.005***	0.000***	0.006***
	(0.0001)	(0.0016)	(0.0001)	(0.0019)	(0.0001)	(0.0022)
Updates	0.450***	0.538***	0.463***	0.624***	0.601***	0.659***
	(0.1085)	(0.0577)	(0.1073)	(0.0562)	(0.1029)	(0.0603)
Intercept	8.327***	9.745***	7.739***	11.113***	5.848***	8.526***
	(2.3408)	(2.4222)	(2.3445)	(2.5223)	(1.5630)	(2.0116)
Observations	5,104	53,944	5,104	53,944	8,125	66,058
R-squared	0.725	0.409	0.744	0.434	0.698	0.410

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

2.7. Summary

This study examines how the performance of the prominent campaigns affects the performance of the less prominent campaigns sharing the same cause within the same crowdfunding platform. In the context of this study, the prominence of a campaign in a particular platform is determined using the order in which the campaign appears on the list of all campaigns sharing the same cause on that platform.

The findings show that market expansion, in the form of more donations from more donors, seems to occur when the prominent campaigns perform well and the non-prominent campaigns appear to benefit from this market expansion. Consequently, the platform also benefits from the superior performance of the prominent campaigns, as the fees received by the platform is an increasing function of the total donations.

The findings from this study have both research and practical implications. From a research perspective, this study shows empirical evidence that supports the theories put forth by Hagiu (2009) and Lin et al. (2016). While this study focuses on philanthropic entities, the economic principles highlighted in this study are likely to be applicable even in commercial settings. Specifically, this study shows that competing campaigns – akin to sellers in commercial settings – steal business from one another, creating a negative same-side effect. The findings show that an increase in the number of campaigns leads to an increase in revenue for the platform. However, the effect is negative on the campaign level, indicating fiercer competition among campaigns when there are more campaigns supporting similar causes on the platform. The findings also suggest that the platform's revenue increases when the prominent campaigns on the platform perform well. Holding the number of campaigns constant, when prominent campaigns perform well, the market expands as more donors enter the platform. In contrast to the negative effect of an increase in the number of campaigns on the platform, when prominent campaigns perform exceptionally well, all campaigns, including the non-prominent campaigns, receive more donations. Due to donor's heterogeneous preferences, once they enter the platform, they search for campaigns that best fit their preferences. As such, even the non-prominent campaigns can benefit from the market expansion created by the exceptional performance of the prominent campaigns. Indeed, I observe both prominent and non-prominent campaigns benefit from the exceptional performance of the prominent campaigns.

The positive externality may be limited in some conditions. For instance, non-prominent campaigns may appear very unattractive to potential donors if the performance gap between the prominent campaigns and the non-prominent campaigns is too extreme. This would eventually result in market domination by the prominent campaigns. Alternatively, the good performance of the prominent campaigns may not generate enough buzz to attract donors into the platform. However, extreme market domination is not typically observed in the current dataset, and therefore, identifying the conditions under which the positive externality is eliminated does not seem plausible in this study. This provides a promising avenue for future studies to explore the limits to the positive externality of prominent campaigns' success highlighted in this study.

From a policymaker perspective, the findings from this study document the positive effect of the non-neutral listing in which sellers who have done better on the platform are subsequently listed more prominently on the platform. By highlighting these sellers, the platform can attract buyers who may eventually purchase from non-prominent sellers. This should mitigate the concern that non-prominent sellers are hurt by such non-neutral listing.

However, one needs to be careful in generalizing this potential positive spill-over effect to ordering mechanisms that do not conform to the RFM methodology that places the sellers who have attracted more buyers more recently on top of the list. Other ranking mechanisms may not attract potential buyers to the platform if the selected prominent sellers do not lend a positive signal to the platform from the perspective of potential buyers. For instance, a reverse listing that places the worse performing sellers on the top of the list may lead to a different effect because such listing is unlikely to motivate potential buyers to participate in the platform.

Moreover, one also needs to note that the positive spill-over effect of market expansion happens only if upon entering the platform, buyers search for sellers that best fit their preferences. A high search cost may prevent potential buyers from searching for sellers that can best match their preferences. To ensure that their non-neutral practices do not hurt non-prominent sellers, platforms can help reduce buyers' search costs by designing their sites in such a way that makes it easy for buyers to search. For example, providing advanced search function within the platform, better keywords search functions, the ability to filter the search list, or a user interface that goes through buyers' preference identification can help lower buyers' search costs. Examining how the different search functions used by platforms can affect the spill-over effect experienced by the less prominent campaigns on the platform seems to be a fertile ground for future studies.

From a practitioner perspective, the findings from this study highlight potentially useful marketing strategies for platforms. More specifically, platforms can benefit from promoting their best performing sellers. Platforms can do so by featuring top performing campaigns on their main landing pages or including the top performing campaigns on their advertisements. Platforms can also design the fee structure in such a way that top performing campaigns pay less in fees. Doing so would provide additional incentives for top fundraisers to enter the platform, and in turn generate positive spill-over effects on other sellers on the platform. I also leave it to future studies to examine the best strategies to incentivize better sellers to enter the market and how those strategies affect the spill-over effect enjoyed by the less prominent sellers on the platforms.

While platforms benefit from having more sellers, platform managers should be cautious in employing aggressive strategies to attract more sellers into the platforms. A higher number of sellers on the same platform may result in more intense competition among these sellers, resulting in a negative same-side effect. This concern should be balanced with the positive cross-side effects of attracting new sellers. In two-sided markets, platforms need to have a critical number of sellers on them to attract buyers (Armstrong, 2006; Rochet & Tirole, 2003). Future studies should be encouraged to examine the optimal number of sellers that a platform needs to have to attract buyers into the platform without hurting the individual sellers that are already on the platform.

Chapter 3 - Birds of a Feather Flock Together (More) in the Age of Trump: Ethnic Homophily in Crowdfunding

3.1 Introduction

One of the main responsibilities of government officials is to set fiscal policies, which include directing the government's public spending. Public spending, including announcements of such spending, can shape the pattern of private transfers. For instance, announcements of public investments in infrastructure can change the pattern of private transfers because those investments are expected to enable private entities to produce goods and services more efficiently (e.g., Bom & Ligthart 2014, Stupak 2018). Do government announcements that are not related to public spending alter the pattern of private transfers too? This study examines how statements from government officials that are not related to public spending change the pattern of private transfers, focusing on the patterns within and across ethnic groups.

The pattern of private transfers examined in this study is in the form of private charitable donations to the relief efforts associated with the major hurricanes hitting the US in 2017. Three major hurricanes – Harvey (category 4), Irma (category 5), and Maria (category 5) – wreaked havoc in the US and surrounding areas during the 2017 Atlantic hurricane season, resulting in the costliest hurricane season on record with billions of dollars of damages (Drye, 2017; Rice, 2017). Recoveries from the damages caused by these hurricanes rely on funding from the US federal government and donations from private donors (Smith, 2017; Kruzel, 2017).

Donations from private donors are traditionally collected by charitable organizations to be delivered to the intended beneficiaries. With the recent advancement of technology, crowdfunding platforms have become viable channels for *individual* fundraisers to collect charitable donations. Indeed, there are 4,464 charitable campaigns on GoFundMe that are initiated by individual fundraisers to provide relief efforts associated with Hurricanes Harvey, Irma, and Maria. These campaigns raised a total of US$25.4 million from 240,270 donors.

This study examines how the pattern of donations from these private donors are influenced by statements from a government official, US President Donald J. Trump. In particular, I ask whether President Trump's statements posted on Twitter regarding the three hurricanes have a disproportionate effect on Hispanic fundraisers and donors on GoFundMe. The dataset on charitable campaigns associated with Hurricanes Harvey, Irma, and Maria provides a suitable setting to explore how public statements from a government official change the pattern of donations within and across ethnic groups for three reasons. First, the dataset contains information on individual donors and fundraisers, which allows for the identification of their ethnicities. Second, the areas affected by these hurricanes have some of the highest percentages of the Hispanic population in the US, resulting in significant proportions of fundraisers and donors with Hispanic ethnicity. Third, President Trump actively posted statements containing information on the hurricanes and the relief efforts associated with those hurricanes on Twitter.

In this study, Hispanic fundraisers are identified based on two criteria: (1) each fundraiser's last name and (2) the language used in the project description (i.e., fundraisers whose project descriptions include a significant portion of Spanish are considered as Hispanic fundraisers), while Hispanic donors are identified using each donor's last name.[12] Using this categorization of ethnicity, a clear pattern of ethnic homophily among fundraisers and donors is observed. Specifically, 20.7% of total donations (as measured in US dollars) received by Hispanic fundraisers came from Hispanic donors, whereas only 4.9% of total donations received by non-Hispanic fundraisers came from Hispanics donors.

The question is how this homophilic pattern changes following statements from a government official. In this study, tweets from President Trump are utilized as shocks to private fundraising efforts associated with the three hurricanes. I hypothesize that President Trump's statements change the pattern of ethnic homophily, in the form of stronger homophily among Hispanics. More specifically, I expect more Hispanic donors contribute more to Hispanic fundraisers following President Trump's statements. This expectation is in line with the documented effects of perceived threats on a group's existential security.[13] As members of a particular ethnic group perceive that their group is threatened, they increase in-group solidarity and close ranks against outsiders to protect their group (Inglehart, Moaddel, & Tessler, 2006; Inglehart & Welzel, 2005).

According to the National Survey of Latino in the US, a large proportion of the randomly surveyed Hispanic respondents view their situation to have worsened since President Trump took office in 2017, with many respondents attributing this to the policies set by the Trump administration (Lopez, Gonzalez-Barrera, & Krogstad, 2018; Rouse & Telhami, 2019).[14] Assuming that the respondents of the

[12] This identification method is consistent with the definition of ethnicity provided by the American Sociological Association. *Ethnicity* is defined as a group of individuals with a shared culture, including language, ancestry, and beliefs (American Sociological Association, n.d.).
[13] *Existential security* refers to the feeling that survival is strong enough that it can be taken for granted (Inglehart et al., 2006).
[14] The National Survey of Latinos is an annual survey conducted nationally in the US by the Pew Foundation. The results and datasets are available on Pew Foundation's website at https://www.pewresearch.org/topics/national-survey-of-latinos/.

National Survey of Latino are representative of the population of Hispanic donors, these donors are likely to have a pre-existing negative perception of President Trump and his administration and therefore view President Trump's statements as threats to their group. As a result, I expect homophily among Hispanics to be stronger following President Trump's statements.

The results from the empirical analyses support the hypothesis that ethnic homophily among fundraisers and donors is stronger following statements from President Trump. Following his tweets, Hispanic fundraisers receive 72% more donations from Hispanic donors. The results also show that President Trump's statements increase donations from Hispanic and non-Hispanic donors regardless of the tone in the messages. This then begs the question of whether his statements simply serve as a reminder to help and that the observed results merely reflect an increase in donations in a homophilic environment, but does not constitute an increase in ethnic homophily. The results from further empirical analyses show that President Trump's statements indeed strengthen homophily among Hispanic donors and fundraisers as the ratio of donations coming from Hispanic donors to Hispanic fundraisers is higher following his tweets.

The rest of Chapter 3 is organized as follows. The theoretical rationale behind the hypotheses put forth in this study is expanded in the next section. The empirical setting and dataset used to test these hypotheses are then discussed in the next sections, followed by the results from the empirical analyses. The chapter is concluded with a discussion of the implications for research, policy, and practice.

3.2 Hypotheses development

How do statements from government officials that are not directly related to the government's public spending change the pattern of private transfers? This study examines how President Trump's statements during the 2017 hurricane season change the pattern of private donations given to charitable campaigns supporting the hurricanes relief efforts, focusing on the ethnicity of the fundraisers and donors.

Homophily, which is a human's tendency to associate with people who are similar to themselves, has been extensively documented in existing studies. McPherson, Smith-Lovin, & Cook (2001) discuss studies that document race/ethnicity-based homophily in various contexts, including marriage (Kalmijn, 1998), friendships (Shrum et al., 1988), and professional relationships (Lincoln & Miller, 1979). In the charitable giving context, Bekkers and Wiepking (2011) posit that potential donors are more likely to provide charitable giving to solicitors they like. As donors are more likely to prefer solicitors who are similar to themselves (Byrne, 1997), including in terms of ethnicity, it seems reasonable to expect ethnic homophily to also exist in the context of charitable giving.

It is within this framework that I focus on the *changes* in ethnic homophily in charitable crowdfunding following statements from President Trump. Existing studies have documented that racial and ethnic homophily appears to persist over time (Smith, McPherson, & Smith-Lovin, 2014; Mollica, Gray, & Trevino, 2003). This study considers a much shorter timeframe, which is 50 days after a natural disaster strikes. As a result, the findings from this study highlight short term changes in ethnic homophily and not long term changes (or lack thereof) as examined by other studies.

Since President Trump took office in 2017, a large proportion of the Hispanic population in the US views their situation to have worsened (Lopez et al., 2018; Rouse & Telhami, 2019). Specifically, 32% of Hispanic respondents of the National Survey of Latinos conducted in 2017 after President Trump took office said that their situation in the US had worsened since the previous year (i.e., compared to their situation in 2016 during the Obama administration). This figure is even higher (47%) in the same survey conducted in 2018. This perceived worsening condition can be attributed to the policies set by the Trump administration (Lopez et al., 2018). Indeed, the 2018 National Survey of Latinos shows that more than half of Hispanic respondents (67%) view the policies set by the Trump administration as being harmful to the Hispanic population in the US. This figure is higher than the results from the same survey conducted in 2010 during the Obama administration (15%) and in 2007 during the Bush administration (41%).

Assuming that the respondents of the National Survey of Latino are representative of the population of Hispanic donors, Hispanic donors are likely to have a negative perception of President Trump and his administration. As such, Hispanic donors are likely to view President Trump's statements as threats, consistent with the *confirmation bias* theory.[15] I expect such perceived threats to strengthen ethnic homophily among Hispanic fundraisers and donors. This expectation is consistent with the findings from existing studies on the effects of perceived threats on a group's existential security. A perceived threat to the survival of a particular ethnic group leads to stronger in-group solidarity. As members of the threaten group focus on the well-being of everyone in the group, they would close

[15] *Confirmation bias* refers to a human's tendency to interpret a piece of information in ways that agree with their prior beliefs (Nickerson, 1998).

ranks against outsiders (Inglehart et al., 2006; Inglehart & Welzel, 2005). Therefore, I hypothesize the following:

Hypothesis 3.1 (the effect of public statements):

Ethnic homophily among Hispanic donors and fundraisers is stronger following statements from President Trump.

The next question is whether the change in homophily is mainly driven by negative statements from President Trump. His negative statements, particularly those targeted directly towards Hispanics, should affect ethnic homophily more than his non-negative (i.e., positive or neutral) statements as those negative statements should be perceived even more as threats to the Hispanic community. Therefore, I hypothesize the following:

Hypothesis 3.2 (the effect of the content of the statement):

The effect of President Trump's statements on ethnic homophily is stronger following a negative statement relative to a non-negative statement.

3.3 Data description

This study utilizes a dataset containing 4,464 charitable campaigns on GoFundMe that support the relief efforts associated with the three major hurricanes that hit the US and its territories in 2017: Harvey (August), Irma (September), and Maria (September). The dataset was collected from August to November 2017 and contains daily data of at least 50 days after the occurrence of each hurricane. The campaigns in the dataset raised a total of US$25.4 million in donations from

240,270 non-anonymous donors. This dataset is a subset of the dataset utilized in the first essay (See Chapter 2 section 2.3).

The three hurricanes in the dataset were selected as part of the dataset for this study for two reasons. First, the areas heavily affected by the three hurricanes are among those with the highest percentage of Hispanic population in the US. Indeed, 99% of the population of Puerto Rico (affected by Hurricane Maria) is Hispanic, whereas the proportions of Hispanic population in Texas and Florida (affected by Hurricanes Harvey and Irma) are 37.6% and 22.5%, respectively (List of U.S. states by Hispanic and Latino population, n.d.). As a result, the dataset contains a significant proportion of fundraisers and donors with Hispanic ethnicities.

Second, these hurricanes are the first major hurricanes affecting the US after President Trump took office in January 2017. In this study, his statements on the three hurricanes are studied as shocks to private fundraising efforts associated with these hurricanes. Specifically, I examine how President Trump's remarks posted on Twitter change the pattern of donations received by Hispanic and non-Hispanic fundraisers.[16]

The dataset also contains daily Federal Emergency Management Agency's (FEMA) press releases and published news articles associated with each of the three hurricanes.[17] These variables are used in the empirical model control for potential confounding effects of public spending announcements (captures in FEMA press releases) and the popularity of each disaster event (captured by the news articles). Table 3.1 reports a summary of the dataset.

[16] President Trump's tweets regarding Hurricanes Harvey, Irma, and Maria were obtained from http://www.trumptwitterarchive.com/, a website that archives President Trump's Twitter messages.
[17] The daily count of English news articles associated with each disaster event was obtained from Factiva database. These counts only include published news articles (i.e., not including articles posted on blogs).

Table 3.1. Dataset summary

	Harvey	Irma	Maria	Total
Number of campaigns	1,635	1,465	1,364	4,464
Non-Hispanic fundraisers	1,476	1,352	875	3,703
Hispanic fundraisers	159	113	489	761
Total donations (USD)	$13,807,829	$5,687,059	$5,993,032	$25,487,920
Number of donors	128,202	51,450	61,218	240,870
Non-Hispanic donors	117,714	48,183	52,001	217,898
Hispanic donors	10,488	3,267	9,217	22,972
Average donation/donor	$107.70	$110.54	$97.90	$105.82
Number of Trump's tweets	26	20	41	87
Number of days Trump tweeted	8	9	11	28
Number of FEMA press releases	15	17	15	47
Number of news articles	37,307	41,558	17,987	96,852
Average number of news articles/day	454.96	506.80	219.35	1,181.12

In this study, the ethnicity of the fundraisers and donors is identified using each individual's last name.[18] Anonymous donors are excluded from the dataset as their ethnicities cannot be determined. The identification of the fundraisers and donors' ethnicities using their last names is suitable in this context as the distinct Hispanic last names provide the fastest and easiest way for donors to identify whether a fundraiser is Hispanic.[19] Additionally, the language used in the project description is also used to determine whether a fundraiser is Hispanic. Natural Language Toolkit (NLTK) in Python is utilized to determine the language used in the project descriptions.[20] Fundraisers who write their project descriptions in

[18] The list of Hispanic last names is obtained from https://names.mongabay.com/data/hispanic.html. This list contains the most common last names for people who self-identified as Hispanics during the 2000 US Census. For the purpose of this study, only a last name with more than 50% of people with that particular last name self-identified as Hispanic is considered as a Hispanic last name.

[19] The process of identifying Hispanic individuals using their last names errs on the side of under-identifying them as Hispanic. For instance, a Hispanic donor with a non-Hispanic last name (e.g., due to marriage) would not be identified as Hispanic.

[20] I use the *stopwords* included in the NLTK library to detect the languages used in a given text. *Stopwords* refer to the most common words in a language that are usually filtered out in natural language processing (Stop words, n.d.). The Python codes to detect languages in a given text are provided by Alejandro Nolla and are available at http://blog.alejandronolla.com/2013/05/15/detecting-text-language-with-python-and-nltk/.

Spanish or in more than one language with one of them being Spanish is considered as Hispanics. The identification of fundraisers' ethnicity using the language in the project description is consistent with the definition of ethnicity, which is a group of individuals with shared culture including language, ancestry, and belief (American Sociological Association, n.d.). Hispanic fundraisers make up 17% of the total fundraisers in the dataset (Figure 3.1). Campaigns associated with Hurricane Maria has the highest proportion of Hispanic fundraisers (35.9%) compared with campaigns associated with the other two hurricanes (9.7% for Hurricane Harvey and 7.7% for Hurricane Irma).

Panel (a) of Figure 3.2 shows that non-Hispanic fundraisers receive very small proportions of their funding from Hispanic donors (4.9%). In contrast, 20.7% of the funding received by Hispanic fundraisers come from Hispanic donors. These patterns indicate an ethnicity driven homophily among fundraisers and donors in charitable crowdfunding. Observing such pattern in the data is not surprising as homophily, including ethnic homophily, have been documented in many settings (as reviewed by McPherson et al., 2001). This homophily is observed in fairly similar magnitudes for all three hurricanes, despite the relatively large variation in the fraction of Hispanics in the affected areas, suggesting that the ethnicity-based homophily observed in this study is likely to be driven by the ethnicity of the fundraisers rather than the ethnicity of the end beneficiaries (as originally posited by Krebs (1975)). In the case of Hurricane Maria that wreaked havoc in Puerto Rico – whose population is 99% Hispanic – 21.7% of the donations received by Hispanic fundraisers came from Hispanic donors (Panel (d) of Figure 3.2). Similarly, 19.5% and 17.0% of the donations received by Hispanic fundraisers came from Hispanic donors in the case of Hurricane Harvey and Irma that heavily affected Texas and

Florida – whose populations are 37.6% and 22.5% Hispanic, respectively (Panels (b) and (c) of Figure 3.2).

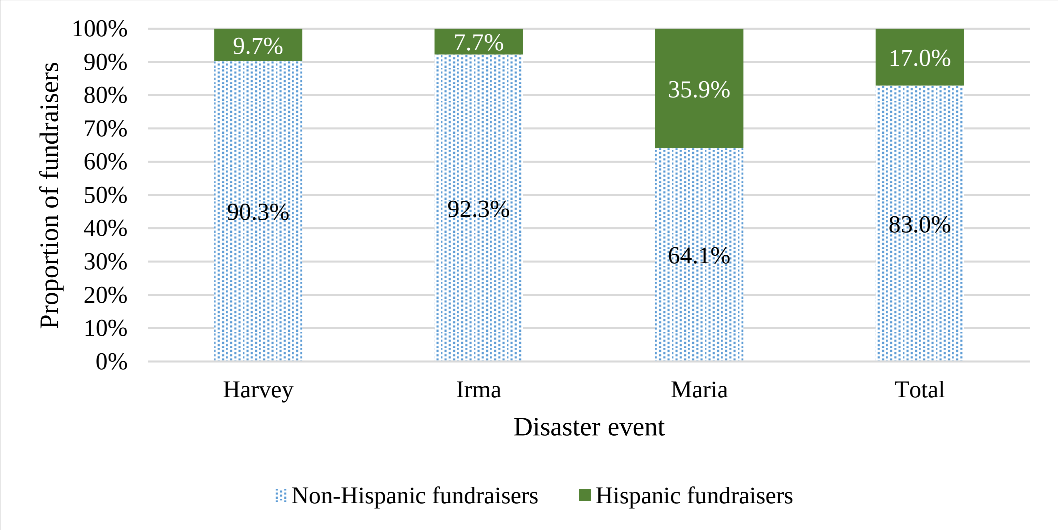

Figure 3.1. Proportions of Hispanic and non-Hispanic fundraisers by event

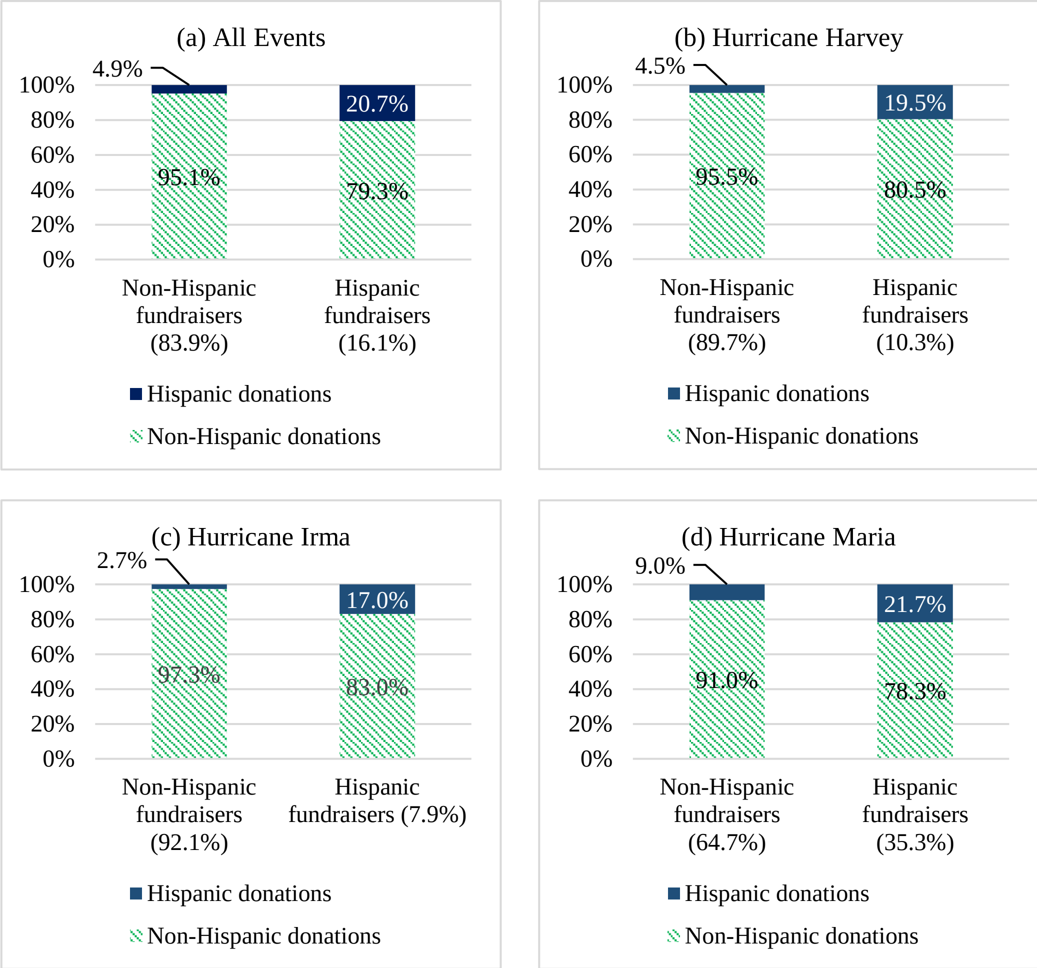

Figure 3.2. Proportions of donations received from Hispanic and non-Hispanic donors by fundraiser ethnicity

3.4 Empirical model

Equation 3.1 describes the empirical model used to test Hypothesis 3.1. The dependent variable is the amount of donations received by campaign *i* on day *t* (in USD). The amount of donations received is logarithmically transformed to reduce its skewness. In the analyses, the amount of donations is separated by the ethnicity of the donors (i.e., from Hispanic and non-Hispanic donors) to examine the presence of ethnic homophily.

$$\ln(Donations)_{i,t} = \alpha_1 * Hispanic_i + \alpha_2 * DJT_{t-1} + \alpha_3 * Hispanic_i * DJT_{t-1} + \mathrm{B} * X + \Theta * Z + \varepsilon \quad (3.1)$$

There are three independent variables of interest in the empirical model. The first variable of interest is *Hispanic*, a binary variable that is set to 1 if fundraiser *i* is categorized as Hispanic and it is set to 0 otherwise. The second variable of interest is *DJT*, a binary variable that is set to 1 if President Trump posts at least one statement on Twitter regarding the relief efforts associated with the hurricane supported by campaign *i* on day *t*, and it is set to 0 otherwise. The final variable of interest is *Hispanic* * *DJT*, the interaction term between *Hispanic* and *DJT*, which is used to examine whether the effect of President Trump's tweet on Hispanic fundraisers differs from that on their non-Hispanic counterparts.

To mitigate potential endogeneity concerns, two sets of control variables are included in the empirical model. The first set of control variables is a vector of time-varying variables (*X*) capturing the characteristics of each event and each campaign that change daily. The second set of control variables is a vector of variables containing the time-invariant characteristics of each campaign (*Z*), which capture the time-invariant heterogeneity across campaigns. In latter specifications, these variables are replaced by campaign fixed effect.

Equation 3.2 describes the empirical model used to test Hypothesis 3.2. Two binary variables are utilized to indicate the tone of President Trump's tweets (*DJTNegative* and *DJTPositive*). One (and only one) of these indicator variables receives the value of 1 during days in which President Trump sends at least one tweet. *DJTNegative* receives the value of 1 if he tweets at least one negative statement on a particular day, and 0 otherwise. *DJTPositive* receives the value of 1 if his tweets on a particular day are categorized as either positive or neutral (i.e., non-negative). Both indicator variables receive the value of 0 if President Trump does not send any tweet on day *t*.

$$\ln(Donations)_{i,t} = \alpha_1 * PuertoRican_i + \alpha_2 * DJTNegative_{t-1} + \alpha_3 * DJTPositive_{t-1} + \alpha_4 * PR_i * DJTNegative_{t-1} + \alpha_5 * PR_i * DJTPositive_{t-1} + \mathrm{B} * X + \Theta * Z + \varepsilon \quad (3.2)$$

In Equation 3.2, Puerto Rican fundraisers and donors are specifically identified because President Trump's negative tweets were specifically targeted towards Hurricane Maria relief efforts in Puerto Rico. Puerto Rican fundraisers and donors are identified by their last names.[21] The binary indicator variable *PuertoRican* is set to 1 for Puerto Rican fundraisers, and 0 for non-Puerto Rican fundraisers. Non-Puerto Ricans include Hispanics whose last names are not commonly used in Puerto Rico. Table 3.2 contains the list of the independent variables included in the empirical models and their respective description and Table 3.3 reports the summary statistics of these variables. All independent variables are measured by the beginning of day *t*, i.e., before the dependent variable is measured.

[21] The list of Puerto Rican last names is obtained from https://forebears.io/puerto-rico#surnames. This list contains the common last names in Puerto Rico based on the birth and death records in Puerto Rico. For the purpose of this study, the frequency of each Puerto Rican last name in Puerto Rico is compared with the frequency of the same last name in the US. Only those last names whose frequency in Puerto Rico is at least 3 times the frequency in the US are considered as Puerto Rican last names.

Table 3.2. Variables description

Variable names	Type	Description
Variables of interest		
Hispanic	Binary	Indicates whether campaign *i*'s fundraiser is Hispanic based on the fundraiser's last name and the language used to describe campaign *i*.
DJT	Binary	Indicates whether on day *t* President Trump posts at least 1 statement on Twitter regarding the disaster event supported by campaign *i*.
*Hispanic*DJT*	Interaction (binary)	An interaction term for a Hispanic fundraiser and whether on day *t* President Trump posts at least 1 tweet regarding the disaster event supported by campaign *i*.
PuertoRican	Binary	Indicates whether campaign *i*'s fundraisers is Puerto Rican based on the fundraiser's last name. The list of last names commonly used in Puerto Rico is a subset of the list of common Hispanic last names.
DJTNegative	Binary	Indicates whether on day *t* President Trump posts at least 1 negative statement on Twitter regarding the disaster event supported by campaign *i*.
DJTPostive	Binary	This indicator variable is set to 1 if on day *t*, President Trump's posts on Twitter regarding the disaster event supported by campaign *i* are not negative (i.e., positive or neutral).
*PuertoRican*DJTNegative*	Interaction (binary)	An interaction term for a Puerto Rican fundraiser and whether on day *t* President Trump posts at least 1 negative tweet regarding the relief efforts associated with the disaster event supported by campaign *i*.
*PuertoRican*DJTPositive*	Interaction (binary)	An interaction term for a Puerto Rican fundraiser and whether on day *t*, President Trump's post(s) on Twitter regarding the relief efforts associated with the disaster event supported by campaign *i* is either positive or neutral.
Time-varying event characteristics		
FEMA	Binary	Indicates whether on day *t*, FEMA publishes at least 1 press release regarding the relief efforts associated with the disaster event supported by campaign *i*.
*Hispanic*FEMA*	Interaction (binary)	An interaction term for a Hispanic fundraiser and whether FEMA publishes at least 1 press release about the relief efforts for the event supported by campaign *i*.
*PR*FEMA*	Interaction (binary)	An interaction term for a Puerto Rican fundraiser and whether FEMA publishes at least 1 press release about the relief efforts for the event supported by campaign *i*.
NumCampaigns	Numeric	The number of campaigns supporting the relief efforts for the same event as campaign *i*. This variable captures the effect of competition.
NewsCount	Numeric	The number of news articles published on day *t* regarding the disaster event supported by campaign *i*. This variable captures the popularity

		of a particular disaster event on a given day. The count only includes published articles in English and does not include blogs.
*Hispanic*NewsCount*	Numeric	An interaction term for a Hispanic fundraiser and the number of news article published on a particular day that are associated with the disaster event supported by campaign *i*. This variable captures the differential effect of news for Hispanic versus non-Hispanic fundraisers.
*PR*NewsCount*	Numeric	An interaction term for a Puerto Rican fundraiser and the number of news article published on day *t* that is associated with the disaster event supported by campaign *i*. This variable captures the differential effect of news for Puerto Rican versus non-Puerto Rican fundraisers.
NewEvent	Binary	Indicates whether it is the first five days since the occurrence of another natural disaster event. This variable captures the potential effect of the arrival of a new disaster event that attracts public interest and distracts potential donors' attention from the event supported by campaign *i*.
Time-varying campaign characteristics		
SMMention	Numeric	The number of social media mentions (Facebook and Twitter) associated with campaign *i*.
Updates	Numeric	The number of updates posted by the fundraiser (Mollick, 2014).
FBFriends	Numeric	The number of Facebook friends the fundraiser has (Lin et al., 2013; Mollick, 2014).
Time-invariant campaign characteristics		
Goal	Numeric	The funding goal set by the fundraiser at the beginning of the campaign (Mollick, 2014).
NumWords	Numeric	The number of words in the project description (Sulaeman & Lin, 2018).
NumVideos	Numeric	The number of videos posted on the campaign's page (Mollick, 2014).
StartTime	Numeric	Indicates when campaign *i* was first posted on the platform (in number of days since the occurrence of the event it supports).
Female	Binary	Indicates whether campaign *i*'s fundraiser is female (Johnson et al., 2018).
FromAffectedArea	Binary	Indicates whether campaign *i*'s fundraiser is located in the state that is directly hit by the disaster event supported by campaign *i* (Mollick, 2014).

Table 3.3. Variables summary statistics

Variable	Mean	Std. Dev.
Donations from non-anonymous donors (USD)	$126.01	$1,711.33
Donations from Hispanic donors	$7.31	$111.54
Donations from non-Hispanic donors	$118.71	$1,662.97
Non-anonymous *donors*	1.13	17.28
Hispanic *donors*	0.10	1.71
Non-Hispanic *donors*	1.03	15.81
Hispanic fundraisers (binary)	0.18	
DJT (binary)	0.15	
Puerto Rican fundraisers (binary)	0.02	
DJTPositive (binary)	0.13	
DJTNegative (binary)	0.02	
FEMA (binary)	0.33	
NumCampaigns	2,282.52	375.30
NewsCount (centered)	0.00	586.05
NewEvent (binary)	0.14	
SMMention	8.55	97.55
Updates	0.06	0.32
FBFriends	740.33	995.84
Goal (USD)	$34,773.55	$695,664.50
NumWords	210.29	156.75
NumVideos	0.14	0.54
StartTime	6.06	5.49
Female (binary)	0.51	
FromAffectedArea (binary)	0.45	

The empirical model is estimated using a panel regression method. Time period clustering is used in the regression to control for within-time-period correlation. Event dummies are also used to control for the heterogeneity across the different disaster events. The correlation matrix and variance inflation factor (VIF) of the dependent variables are included in Appendix D. They indicate that multicollinearity is not a concern in this study.

3.5 Empirical analyses

3.5.1. The effects of President Trump's statements on the pattern of donations

Table 3.4 reports the results from the regressions estimating the empirical model in Equation 3.1. The regressions were estimated three times, each with a different dependent variable: donations received by campaign *i* from Hispanic donors at time *t* (Column 1), donations received by campaign *i* from non-Hispanic donors at time *t* (Column 2), donations (in USD) received by campaign *i* from non-anonymous donors (i.e., Hispanic and non-Hispanic donors) at time *t* (Column 3). The positive parameter estimate for *Hispanic* in Column 1 indicates that Hispanic fundraisers receive 20% more donations from Hispanic donors compared to non-Hispanic fundraisers.[22] In contrast, the negative estimate in Column 2 indicates that Hispanic fundraisers receive 19% less donation from non-Hispanic donors compared to non-Hispanic fundraisers.[23] These results confirm the pattern of ethnic homophily shown in Figure 3.2. It is also important to note that the estimate for *Hispanic* in Column 3 is not significant. This suggests that Hispanic fundraisers do not operate at a disadvantage in terms of their ability to raise funds.

The results in Table 3.4 suggests that ethnic homophily is stronger following President Trump's tweets, supporting Hypothesis 3.1. The significant positive estimates for *Hispanic*DJT* in Column 1 indicates that the amount of donations from Hispanic donors to Hispanic fundraisers increases by 72% following tweets

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[22] The amount of donations received by Hispanic fundraisers from Hispanic donors is 1.20 (=exp(0.188618)) times the amount of donations received by non-Hispanic fundraisers from Hispanic donors.

[23] The amount of donations received by Hispanic fundraisers from non-Hispanic donors is 0.81 (=exp(-0.216810)) times the amount of donations received by non-Hispanic fundraisers from non-Hispanic donors.

from President Trump.[24] In contrast, the amount of donations from Hispanic donors to non-Hispanic fundraisers does not seem to change following his tweets (see the insignificant estimate for *DJT* in Column 1).

The results in Column 2 of Table 3.4 show that President Trump's tweets have a different effect on the pattern of donations from non-Hispanic donors. Non-Hispanic donors more than double their donations to non-Hispanic fundraisers following his tweets (as shown by the significant positive estimate of *DJT* in Column 2).[25] However, more importantly, the amount of donations from non-Hispanic donors to Hispanic fundraisers also increases in the same magnitude as indicated by the non-significant estimate of *Hispanic*DJT* in Column 2. These findings suggest that President Trump's statements may have served as repeat reminders to give, particularly for non-Hispanic donors.

It is also important to note that while I find significant effects of President Trump's tweets on donations, the results show that announcements of government relief effort funding through a more official communication channel (for instance, through FEMA press releases) do not significantly affect private donations. The estimates for *FEMA* and *Hispanic*FEMA* are not significant in Columns 1, 2, and 3. This is likely because FEMA is perceived as a neutral entity and therefore, does not incite a response from donors that strengthen ethnic homophily among Hispanic donors and fundraisers. However, the count of news articles (*NewsCount* and *Hispanic*NewsCount*) seems to affect the amount of donations in the same direction as President Trump's tweets. It is possible that the effect of President

[24] The amount of donations from Hispanic donors received by Hispanic fundraisers went up 1.72 (=exp(0.543824)) times following President Trump's tweets.
[25] Total donations per campaign went up 2.82 (=exp(1.037171)) times following President Trump's tweets.

Trump's tweets is partly absorbed by the published news articles as his tweets are often covered by published news media (Cillizza, 2017; Diaz, 2017).

Table 3.4. The effects of President Trump's tweets on ethnic homophily

VARIABLES	(1) ln(*Donations from Hispanic donors*)	(2) ln(*Donations from non-Hispanic donors*)	(3) ln(Total *Donations*)
Variable of interest			
Hispanic	0.187618***	-0.216810*	-0.136580
	(0.055779)	(0.117227)	(0.122465)
DJT	0.058323	1.037171**	1.026460*
	(0.134921)	(0.506546)	(0.528759)
*Hispanic*DJT*	0.543824***	0.114649	0.294869
	(0.162154)	(0.365887)	(0.375600)
Event characteristics			
FEMA	-0.027024	0.123326	0.124279
	(0.047385)	(0.217099)	(0.223715)
*Hispanic*FEMA*	-0.041114	-0.326521	-0.338350
	(0.110445)	(0.214268)	(0.227416)
NumCampaigns	-0.001127**	-0.001582	-0.001981
	(0.000501)	(0.001526)	(0.001655)
NewsCount	0.000119	0.001449***	0.001423***
	(0.000099)	(0.000301)	(0.000316)
*Hispanic*NewsCount*	0.000607***	0.000136	0.000288
	(0.000149)	(0.000241)	(0.000267)
NewEvent	0.150112	1.207786***	1.237682***
	(0.092415)	(0.275248)	(0.287741)
Time-varying campaign characteristics			
SMMention	0.004473***	0.005725***	0.005685***
	(0.000877)	(0.001434)	(0.001427)
Updates	0.446850***	1.614301***	1.630736***
	(0.080168)	(0.100970)	(0.105473)
FBFriends	0.000036***	-0.000043**	-0.000039**
	(0.000011)	(0.000018)	(0.000019)
Time-invariant campaign characteristics			
ln(*Goal*)	0.137836***	0.528565***	0.538613***
	(0.013855)	(0.036552)	(0.036861)
NumWords	0.000222***	0.001191***	0.001224***
	(0.000068)	(0.000159)	(0.000158)
NumVideos	0.002475	0.058440*	0.048156
	(0.019880)	(0.029610)	(0.031577)
StartTime	0.013524***	0.081294***	0.087372***
	(0.002477)	(0.009134)	(0.009551)
Female	0.025686*	0.065616**	0.056745*

	(0.014559)	(0.030922)	(0.030865)
FromAffectedArea	0.091250***	-0.073495**	-0.048904
	(0.021234)	(0.035776)	(0.037343)
Intercept	-5.469633***	-7.292873**	-6.443342
	(1.198979)	(3.611264)	(3.915150)
Observations	59,062	59,062	59,062
R-squared	0.111	0.205	0.209

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Event dummies and time error clustering are included in the regressions. All independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

3.5.2 The effects of negative statements on pattern of donations

The next question is whether the results observed in the previous section are driven primarily by President Trump's negative statements. During the 2017 hurricane season, President Trump directed several negative statements on Twitter towards the local government in Puerto Rico, in which he accused them of doing a poor job in handling the aftermath of Hurricane Maria (Cillizza, 2017; Diaz, 2017). Given President Trump's specific target for his negative tweets, the empirical analyses to test Hypothesis 3.2 uses a subset of the dataset containing only campaigns associated with Hurricane Maria, the main target of Trump's negative tweets. Campaigns associated with Hurricanes Harvey and Irma are not utilized for these analyses as President Trump did not post any negative statements regarding the relief efforts associated with these two hurricanes.

The significant positive estimates for *PR*DJTNegative* and *PR*DJTPositive* in Column 1 of Table 3.5 suggest that ethnic homophily among Hispanic donors and fundraisers is stronger following President Trump's negative as well as positive/neutral tweets.[26] This finding does not support Hypothesis 3.2, indicating

[26] Following President Trump's non-negative tweets, the amount of donations from Puerto Rican donors give 44% more to Puerto Rican fundraisers (exp(0.311192+0.054215)=1.44) than to non-Puerto Rican fundraisers. This is 37% more donations Puerto Rican donors to Puerto Rican fundraisers compared to before President Trump's non-negative tweets (exp(0.311192)=1.37). Following President Trump's negative tweets, Puerto Rican donors give 50% more to Puerto Rican fundraisers (exp(0.354609+0.054215)=1.50) than to non-Puerto Rican fundraisers. This is 43%

that the negative statements do not have a disproportionate effect on donation patterns. It is important to note that the results in this table are also consistent with the potential explanation that President Trump's tweets serve as reminders to give to the cause. Indeed, negative tweets from President Trump also appear to increase the amount of donations from non-Puerto Rican donors to Puerto Rican fundraisers. The next section explores this alternative explanation in more detail.

Table 3.5. Hurricane Maria: Homophily in charitable crowdfunding after President Trump's negative and positive tweets

	(1)	(2)	(3)
VARIABLES	ln(*Donations from Puerto Rican donors*)	ln(*Donations from non-Puerto Rican donors*)	ln(*Total Donations*)
Variable of interest			
PuertoRican	0.054215	0.478499**	0.486871*
	(0.055072)	(0.236211)	(0.253356)
DJTPositive	-0.090678*	-0.065790	-0.088376
	(0.047405)	(0.641449)	(0.647095)
*PR*DJTPositive*	0.311192*	-0.750081	-0.693036
	(0.153901)	(0.473474)	(0.490111)
DJTNegative	-0.014558	1.157785	1.138857
	(0.040216)	(1.068477)	(1.055589)
*PR*DJTNegative*	0.354609***	0.923519***	1.317599***
	(0.091636)	(0.294215)	(0.317510)
Event characteristics			
FEMA	0.008207	-0.178540	-0.179601
	(0.031459)	(0.300961)	(0.302634)
*PR*FEMA*	-0.054453	0.111287	0.075403
	(0.085308)	(0.280796)	(0.288932)
NumCampaigns	-0.000331	-0.003161	-0.003312
	(0.000293)	(0.002500)	(0.002529)
NewsCount	0.000301	0.006226***	0.006216***
	(0.000179)	(0.001433)	(0.001444)
*PR*NewsCount*	0.000099	0.001608	0.001647
	(0.000196)	(0.001108)	(0.001136)
Time-varying campaign characteristics			
SMMention	0.005235***	0.008868***	0.008855***
	(0.000720)	(0.001198)	(0.001199)
Updates	0.152036*	1.706319***	1.688321***

more donation from Puerto Rican donors to Puerto Rican fundraisers compared to before President Trump's negative tweets (exp(0.354609)=1.43).

	(0.075925)	(0.131074)	(0.132371)
FBFriends	0.000091***	0.000130***	0.000126***
	(0.000021)	(0.000034)	(0.000035)
Time-invariant campaign characteristics			
ln(*Goal*)	0.051786***	0.547474***	0.552058***
	(0.010815)	(0.041160)	(0.040674)
NumWords	0.000001	0.001785***	0.001771***
	(0.000063)	(0.000266)	(0.000266)
NumVideos	-0.019850	0.177809***	0.173322***
	(0.019007)	(0.059016)	(0.059460)
StartTime	0.006553***	0.088703***	0.090764***
	(0.002054)	(0.011777)	(0.011790)
Female	0.002088	0.083900	0.077395
	(0.019708)	(0.052933)	(0.053644)
FromAffectedArea	-0.046742	-0.271935***	-0.254965***
	(0.028959)	(0.068044)	(0.070788)
Intercept	-6.752114***	-4.957053	-4.704862
	(0.526619)	(4.379669)	(4.433201)
Observations	17,291	17,291	17,291
R-squared	0.118	0.231	0.231

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Event dummies and time error clustering are included in the regression. All independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

3.5.3 The effect of President Trump's statements on the ratio of donations from Hispanic donors

The findings in the previous sections beg the question of whether the effects documented in Tables 3.4 and 3.5 merely reflect an increase in donations in a homophilic environment due to the buzz created by President Trump's tweets, which can serve as reminders for potential donors to give. I argue that the results presented in Table 3.4 suggest that the effects of President Trump's statements go beyond creating buzz around the disaster relief efforts; his statements change the underlying pattern of the donations. While in sum President Trump's tweets have a positive effect on the amount of donations (see the positive estimate of *DJT* in Column 3 of Table 3.4), the effects of his tweets on donations from non-Hispanic donors (Column 2) differ from the effects on donations from Hispanic donors

(Column 1). If it is indeed the case that the effects of President Trumps are only increasing donations in an already homophilic environment, then similar effects should have been observed for Hispanic and non-Hispanic donors.

To test this hypothesis, an additional regression was performed to examine how President Trump's tweets affect the proportion of donations from Hispanic donors. In this regression, the outcome variable is changed to *HispanicRatio_amount*, which is the ratio of the amount of donation from Hispanic donors over the total donation received by campaign *i* on day *t*. If indeed President Trump's statements increase donations without changing the underlying pattern of the donations, then I expect the proportion of donations from Hispanic donors to not change following his statements.

The significant positive estimate for *Hispanic*DJT* indicates that the proportion of donations from Hispanic donors received by Hispanic fundraisers increases following President Trump's statements (Table 3.6). In contrast, the proportion of donations from Hispanic donors to non-Hispanic fundraisers does not significantly change following his statements (see the non-significant estimate for *DJT*). These findings suggest that ethnic homophily among Hispanic donors and fundraisers is indeed stronger following President Trump's tweets. The stronger ethnic homophily among Hispanic donors and fundraisers may be driven by an increase in solidarity among Hispanics triggered by President Trump's tweets.

Table 3.6 The effect of President Trump's statements on the ratio of donations from Hispanic donors

VARIABLES	*HispanicRatio_amount*
Variable of interest	
Hispanic	0.013053***
	(0.002506)
DJT	-0.000156
	(0.005179)
*Hispanic*DJT*	0.022626***
	(0.007198)
Event characteristics	
FEMA	-0.000207
	(0.001532)
*Hispanic*FEMA*	-0.001645
	(0.005374)
NumCampaigns	-0.000064***
	(0.000021)
NewsCount	-0.000003
	(0.000003)
*Hispanic*NewsCount*	0.000035***
	(0.000006)
NewEvent	0.005630*
	(0.003091)
Time-varying campaign characteristics	
SMMention	0.000023***
	(0.000008)
Updates	0.009301***
	(0.002022)
FBFriends	0.000001***
	(0.000001)
Time-invariant campaign characteristics	
ln(*Goal*)	0.002509***
	(0.000334)
NumWords	0.000006*
	(0.000003)
NumVideos	-0.000468
	(0.000837)
StartTime	0.000776***
	(0.000132)
Female	-0.000309
	(0.000741)
FromAffectedArea	0.003688***
	(0.001002)

Intercept	0.126344**
	(0.050446)
Observations	59,062
R-squared	0.037

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Event dummies and time error clustering are included in the regression. All independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

3.6 Robustness checks

3.6.1 Campaign fixed effects

In the crowdfunding context, project characteristics have been documented as determinants of how successful a campaign is in raising funds (e.g., Mollick, 2014). Campaign fixed effects can be utilized to capture the various time-invariant project characteristics that may influence campaigns' performance. Table 3.7 reports the regression results with campaign fixed effect. The time-invariant variables are excluded from these regressions as they are captured by the campaign fixed effect. The effect of President Trump's statements on ethnic homophily documented in Table 3.4 remains robust with campaign fixed effects included in the regressions.

Table 3.7. The effects of President Trump's tweets on ethnic homophily, with campaign fixed effect

VARIABLES	(1) ln(*Donations from Hispanic donors*)	(2) ln(*Donations from non-Hispanic donors*)	(3) ln*(Total Donations)*
	Variable of interest		
DJT	-0.180860*	0.342281	0.290558
	(0.097017)	(0.300629)	(0.307903)
*Hispanic*DJT*	0.559375***	0.151852	0.352102
	(0.181048)	(0.276254)	(0.276656)
	Event characteristics		
FEMA	-0.030777	0.085953	0.078654
	(0.035070)	(0.111485)	(0.114459)
*Hispanic*FEMA*	0.016948	-0.142417	-0.125814
	(0.094997)	(0.128252)	(0.131538)
NumCampaigns	-0.003980***	-0.011451***	-0.012352***

	(0.000602)	(0.001282)	(0.001390)
NewsCount	-0.000005	0.001459***	0.001401***
	(0.000092)	(0.000224)	(0.000229)
*Hispanic*NewsCount*	0.000870***	-0.000125	0.000135
	(0.000165)	(0.000221)	(0.000238)
NewEvent	-0.072663	0.238126	0.234410
	(0.074999)	(0.188175)	(0.195435)
Time-varying campaign characteristics			
SMMention	0.002904***	0.001343***	0.001225***
	(0.000479)	(0.000292)	(0.000273)
Updates	0.205480***	0.891863***	0.877636***
	(0.061917)	(0.075410)	(0.075044)
FBFriends	-0.000626***	-0.001128***	-0.001191***
	(0.000168)	(0.000242)	(0.000249)
Intercept	3.063464**	21.765096***	23.975066***
	(1.369955)	(2.988065)	(3.232796)
Observations	59,062	59,062	59,062
R-squared	0.333	0.472	0.478

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Campaign fixed effect and time error clustering are included in the regressions. All independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

3.6.2 The effect of President Trump's statements on the number of donors

To further check for the robustness of the results, I modify the outcome variable in our empirical model to the number of donors, instead of the amount of donations. The results of the regressions using the alternate model are shown in Table 3.8. The effect of President Trump's statements on ethnic homophily remains robust with the alternate outcome variables.

Table 3.8. The effects of President Trump's tweets on the number of donors

VARIABLES	(1) ln(*Hispanic Donors*)	(2) ln(N*on-Hispanic Donors*)	(3) ln(*Total Donors*)
Variable of interest			
Hispanic	0.120221***	-0.136123*	-0.082305
	(0.036110)	(0.075043)	(0.078571)
DJT	0.034754	0.666737**	0.663073*
	(0.088205)	(0.328047)	(0.343277)
*Hispanic*DJT*	0.365352***	0.077885	0.200212
	(0.108297)	(0.237149)	(0.243909)

Event characteristics			
FEMA	-0.019315	0.077170	0.077123
	(0.030791)	(0.139369)	(0.143949)
*Hispanic*FEMA*	-0.023774	-0.216259	-0.224323
	(0.073473)	(0.137534)	(0.147314)
NumCampaigns	-0.000744**	-0.001116	-0.001383
	(0.000326)	(0.000991)	(0.001078)
NewsCount	0.000076	0.000933***	0.000918***
	(0.000064)	(0.000195)	(0.000205)
*Hispanic*NewsCount*	0.000392***	0.000102	0.000206
	(0.000097)	(0.000155)	(0.000173)
NewEvent	0.097021	0.764694***	0.785677***
	(0.059744)	(0.177836)	(0.186541)
Time-varying campaign characteristics			
SMMention	0.003098***	0.004178***	0.004170***
	(0.000581)	(0.001001)	(0.001001)
Updates	0.292059***	1.075341***	1.089040***
	(0.053511)	(0.069643)	(0.072834)
FBFriends	0.000027***	-0.000018	-0.000015
	(0.000007)	(0.000012)	(0.000012)
Time-invariant campaign characteristics			
ln(*Goal*)	0.089566***	0.334760***	0.342306***
	(0.008973)	(0.023297)	(0.023539)
NumWords	0.000144***	0.000785***	0.000807***
	(0.000044)	(0.000103)	(0.000102)
NumVideos	0.005874	0.043119**	0.038084*
	(0.013218)	(0.019749)	(0.021088)
StartTime	0.008681***	0.052430***	0.056446***
	(0.001597)	(0.005936)	(0.006211)
Female	0.013898	0.038789*	0.033091*
	(0.009404)	(0.019662)	(0.019662)
FromAffectedArea	0.059718***	-0.052886**	-0.035828
	(0.014005)	(0.023230)	(0.024268)
Intercept	-5.946138***	-6.887694***	-6.328452**
	(0.778664)	(2.344065)	(2.549369)
Observations	59,062	59,062	59,062
R-squared	0.117	0.213	0.216

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Event dummies and time error clustering are included in the regression. All independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

3.7 Summary

This study contributes to the literature across multiple disciplines. First, this study documents the effects of statements from a government official on the pattern of private transfers even when the statements are not related to public spending. In particular, statements from a government official who is perceived negatively by members of a certain ethnic group appear to increase the solidarity within the group in the form of an increase in the proportion of donations coming from members of that ethnic group. The direction of the change in the homophily seems to be driven primarily by the group's pre-existing view of the official. However, it is important to not some caveats here. In this study, the respondents of the National Survey of Latinos are assumed to be representative of the population of Hispanic donors. A more direct measure of donors' perceptions and attitudes is not feasible in this study due to data limitation. It is also important to note that President Trump, whose statements are the focus of this study, is quite unique in his controversial stands on many issues and his extensive use of social media to deliver his political rhetoric. It would be useful to examine other political figures or media influencers – with different images and reputations – to generalize the results in this study.

Second, to the best of my knowledge, this is the first study that documents ethnic homophily among fundraisers and donors in the context of charitable giving. Traditional charitable fundraising data do not usually allow for the identification of the ethnicity of the fundraisers as each individual fundraiser's identity is often not recorded and therefore unobserved by researchers. For practitioners, this study highlights the importance of targeted appeals to potential donors, particularly when making appeals to donors with different ethnicities. In line with the finding that donors are likely to respond more positively to fundraisers who appear to be more similar to them, marketing practitioners and charitable fundraisers should pay closer attention to the cultural background and ethnicity of their targeted donors. While the language used in the solicitation could help charities to appeal to a certain ethnic group, the ethnicity of the person soliciting for donations could also influence the success of the fundraising campaign.

Lastly, while homophily does not seem to place the minority group at a disadvantage in this setting, other studies have documented that a higher degree of homophily can have a negative effect on the minority groups in a social network (Karimi et al., 2018). Even though the findings from this study show that the total donations received by Hispanic fundraisers is not significantly different than the total donations received by their non-Hispanic counterparts, I find that the average donation size from Hispanic donors ($74.46) is lower than the average donation size from non-Hispanic donors ($109.12). This suggests that stronger homophily could put minority fundraisers at a disadvantage, consistent with Karimi et al. (2018).

Increasing interactions across ethnic groups may help counter the potential negative effect of homophily on minority fundraisers, assuming that this increase in interactions across groups would lead to the majority and minority donors contributing to campaigns regardless of the ethnicity of the fundraisers. With the increased interactions across ethnic groups, donors from the majority groups would increase the support for the minority fundraisers. One potential way to mitigate donors' homophilic preferences is to anonymize the fundraisers as their ethnicities can be easily identified using their last names. However, this strategy is not without drawbacks. One important drawback to consider is the potential negative effect of anonymizing fundraisers on donors' trust and ultimately on their willingness to donate.

Chapter 4 – Concluding Remarks

Platforms that enable interactions among various economic agents play a key role in the digital economy as gatekeepers for access to contents and trades online. Therefore, it is not surprising that more and more economic agents participate in the platform economy. With the continuous growth of digital platforms, it is important to examine which factors influence the welfare of the different economic agents participating in the platform economy.

This dissertation contributes to the growing literature on platform economy. The first essay explores the consequences of non-neutral practices on digital platforms, particularly in regard to listing certain campaigns more prominently than other campaigns within the platform. The findings from the first essay should mitigate the concern that non-neutral platforms' practices naturally lead to an outcome that could hurt sellers, buyers, and ultimately the platform itself. The first essay also offers some insights on potentially effective platforms' strategies to increase their revenues while minimizing the negative effect of competition among similar campaigns on these platforms.

The first essay is limited to only one crowdfunding platform, focusing on charitable fundraising. Future studies should explore the issue of non-neutral listing practices on more platforms, beyond charitable crowdfunding and even beyond crowdfunding platforms. Studies on other platforms, such as e-commerce marketplaces may find different results particularly when the products are more tangible and easier to differentiate. The first essay should also encourage future studies that could enhance the findings, including studies that explore ways to incentivize better sellers to enter a platform and studies that explore ways that lower the search costs faced by buyers when identifying the best fit for their individual preferences. Additionally, the first essay highlights the importance of future studies on whether promoting certain types of fundraisers, for example, serial fundraisers who have been successful in the past, can entice potential donors or funders to come into the platform.

The second essay documents how public statements from government officials on social media can change the pattern of private transfers. Direct or personal statements from an individual government official, particularly through communication channels that reach a wide set of audiences, may carry unintended consequences as the resulting public reactions may be driven by the pre-existing view of that government official instead of the content of the message. The findings from the second essay suggest that President Trump’s statements seems to have a positive effect on private donations. However, this fortunate side effect comes with an increase in same ethnicity preference. If the government’s objective is to disseminate important information to the public, it could use a more neutral communication channel to prevent the negative side effects.

Similar to the first essay, the second essay is also limited by its setting. More specifically, the study focuses on statements from one particular government official and the effects of these statements on donations to support the relief efforts associated with major Atlantic hurricanes. Public statements from government officials other than President Trump may not have the same effect on public transfers because President Trumps is quite unique in his controversial stands on many issues and his extensive use of social media to deliver his political rhetoric. The second essay should encourage future studies on the effects of public statements from other government officials as well as other public figures, such as celebrities, on private transfers. Future studies on the effects of public statements from other public figures, particularly from the social media influencers who are not politicians, may further substantiate the theoretical background utilized to support the hypothesis in Essay 2. If futures studies find that statements from other public figures who are not perceived as threats to minority groups (or if they come from minority groups) have weaker (or no) effect on ethnic homophily, this will validate and strengthen my conclusion. Additionally, future studies should also explore the effect of statements posted on social media on other types of private transfers, such as household spending and savings. Additionally, detailed (textual) analysis of the contents of the messages, particularly if the messages are longer, can be performed to enrich the findings.

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Appendices for Chapter 2

Appendix A. Multicollinearity checks for Chapter 2

Table A.1 shows the correlations matrix of the dependent variables in the empirical models in Chapter 2. Table A.2 shows the variance inflation factors (VIF) for those variables. The correlation matrix and the VIF indicate that multicollinearity is not a concern for the regressions in Chapter 2.

Table A.1. Correlation matrix of the independent variables

		1	2	3	4	5	6	7
1	*EarnRatio_45*	1.00						
2	*NumCampaigns*	-0.25	1.00					
3	*MetGoal_45*	-0.40	0.78	1.00				
4	*NewEvent*	0.08	0.17	0.10	1.00			
5	*NewsCntr*	0.56	-0.13	-0.24	0.14	1.00		
6	*SocMedia*	0.09	0.00	-0.04	0.01	0.09	1.00	
7	*Updates*	0.16	-0.04	-0.07	0.04	0.14	0.12	1.00

Table A.2. Variance inflation factor (VIF) of the independent variables

Variable	VIF	1/VIF
MetGoal_45	2.86	0.35
NumCampaigns	2.61	0.38
EarnRatio_45	1.65	0.61
NewsCntr	1.48	0.67
NewEvent	1.06	0.94
Updates	1.04	0.96
SocMedia	1.02	0.98
Mean VIF	1.68	

Appendix B. The effect of a change in the performance of the prominent campaigns on themselves

Table B.1 shows the parameter estimates for the regressions where the dependent variables are the amount of donations received by (Column 1) and the number of donors contributing to (Column 2) the first 45 campaigns on the list (i.e., prominent campaigns. The results show that the exceptional performance of the prominent campaigns has a positive effect on themselves in the next period.

Table B.1. The effect of the change in the relative performance of prominent campaigns on themselves

	Prominent campaigns (first 45)	
	(1)	(2)
VARIABLES	ln(*Donations*)	ln(*Donors*)
EarnRatio_rk45	6.660***	4.277***
	(0.7964)	(0.5154)
NumCampaigns	-0.008***	-0.006***
	(0.0014)	(0.0010)
Top45goalmet_ratio	-4.422*	-2.749*
	(2.3411)	(1.5670)
NewEvent	0.821**	0.511**
	(0.3592)	(0.2482)
NewsCntr	0.002***	0.001***
	(0.0004)	(0.0003)
SocMedia	0.000	0.000***
	(0.0001)	(0.0001)
Updates	0.887***	0.601***
	(0.1486)	(0.1029)
Intercept	9.774***	5.817***
	(2.2997)	(1.5639)
Observations	8,118	8,125
R-squared	0.681	0.698

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parentheses is clustered by time period. Campaign fixed effect is included in the regression. The independent variables are measured by the beginning of day t, i.e., before the dependent variable is measured.

Appendix C. Subset dataset containing only first-time donors

Table C.1 reports the summary statistics of the variables in the subset dataset containing only first-time donors supporting the relief efforts associated with Hurricanes Harvey, Irma, and Maria.

Table C.1. Summary statistics of the variables in the subset dataset

Variable	Mean	Std. dev
Donations from first-time donors (USD)	$117.51	$1,452.41
First-time donors	1.07	16.80
Earn ratio of first 45 campaigns	0.25	0.15
Percentage of first 45 that have met/exceeded their funding goals	0.28	0.13
Number of campaigns	2282.52	375.30
Number of news articles	454.07	566.84
Social media mentions	5.66	82.19
Number of updates	0.04	0.27

Appendices for Chapter 3

Appendix D. Multicollinearity checks for Chapter 3

Table D.1 and Table D.2 display the correlations matrices of the dependent variables in the models in Chapter 3. Table D.3 and Table D.4 display the variance inflation factors (VIF) for those variables. The correlation matrix and the VIF indicate that multicollinearity is not a concern for the regressions in Chapter 3.

Table D.1. Correlation matrix of the independent variables in the regressions using the full dataset

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	*Hispanic*	1.00																	
2	*DJT*	0.04	1.00																
3	*Hispanic*DJT*	0.39	0.43	1.00															
4	*FEMA*	0.01	0.10	0.00	1.00														
5	*Hispanic*FEMA*	0.55	0.02	0.21	0.36	1.00													
6	*NumCampaigns*	-0.30	-0.39	-0.25	-0.07	-0.18	1.00												
7	*NewsCount* (centered)	-0.01	0.45	0.10	0.08	0.00	-0.33	1.00											
8	*Hispanic*NewsCount*	0.01	0.20	0.40	0.02	0.03	-0.11	0.26	1.00										
9	*NewEvent*	-0.05	-0.12	-0.04	0.03	-0.01	0.06	0.18	0.10	1.00									
10	*SocMedia*	-0.01	0.11	0.03	0.02	0.00	-0.06	0.10	0.03	0.01	1.00								
11	*Updates*	0.01	0.15	0.06	0.02	0.00	-0.12	0.16	0.07	0.04	0.12	1.00							
12	*FBFriends*	-0.05	-0.02	-0.02	0.00	-0.03	0.07	-0.02	-0.01	0.00	0.01	0.00	1.00						
13	ln(*Goal*)	0.00	0.02	0.00	0.00	0.00	-0.01	0.03	0.03	0.00	0.01	0.01	0.00	1.00					
14	*NumWords*	-0.01	-0.03	-0.01	0.00	0.00	0.01	-0.05	-0.01	-0.01	0.02	0.04	0.01	0.00	1.00				
15	*NumVideo*	-0.01	0.00	0.00	0.00	-0.01	-0.02	-0.01	0.01	-0.01	0.01	0.02	0.10	0.01	0.04	1.00			
16	*StartTime*	0.02	-0.16	-0.04	-0.01	0.02	0.01	-0.26	-0.09	-0.10	-0.03	-0.01	-0.04	-0.02	0.11	0.02	1.00		
17	*Female*	-0.01	-0.02	-0.01	-0.01	0.00	0.04	-0.02	0.00	0.01	0.01	0.01	-0.02	-0.01	0.00	-0.05	0.05	1.00	
18	*FromAffectedArea*	-0.05	-0.10	-0.07	-0.03	-0.04	0.33	-0.05	-0.02	0.06	0.01	-0.02	0.04	0.00	-0.02	0.01	0.02	0.01	1.00

Table D.2. Correlation matrix of the independent variables in the regressions using the subset dataset (Hurricane Maria)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	*PuertoRican*	1.00																		
2	*DJTPositive*	0.00	1.00																	
3	*PR*DJTPositive*	0.37	0.14	1.00																
4	*DJTNegative*	0.02	-0.05	-0.01	1.00															
5	*PR*DJTNegative*	0.19	-0.01	0.00	0.22	1.00														
6	*FEMA*	0.00	0.13	0.01	-0.09	-0.02	1.00													
7	*PR*FEMA*	0.58	0.01	0.25	-0.01	0.00	0.12	1.00												
8	*NumCampaigns*	-0.11	-0.35	-0.08	-0.18	-0.04	-0.07	-0.07	1.00											
9	*NewsCount* (centered)	-0.01	0.47	0.03	0.01	0.00	0.08	-0.01	-0.33	1.00										
10	*PR*NewsCount*	-0.09	0.07	0.39	0.01	0.04	0.01	-0.01	-0.04	0.09	1.00									
11	*SocMedia*	0.00	0.12	0.01	0.00	0.00	0.02	0.00	-0.06	0.10	0.01	1.00								
12	*Updates*	0.00	0.16	0.02	0.01	0.01	0.02	0.00	-0.12	0.16	0.02	0.12	1.00							
13	*FBFriends*	-0.02	-0.02	-0.01	-0.02	0.00	0.00	-0.01	0.07	-0.02	0.00	0.01	0.00	1.00						
14	ln(*Goal*)	-0.01	0.02	0.00	0.00	0.00	0.00	0.00	-0.01	0.03	0.00	0.01	0.01	0.00	1.00					
15	*NumWords*	-0.02	-0.04	-0.01	0.01	0.00	0.00	-0.01	0.01	-0.05	0.00	0.02	0.04	0.01	0.00	1.00				
16	*NumVideo*	-0.01	0.00	-0.01	0.00	0.00	0.00	-0.01	-0.02	-0.01	-0.01	0.01	0.02	0.10	0.01	0.04	1.00			
17	*StartTime*	0.02	-0.17	-0.01	0.00	0.00	-0.01	0.01	0.01	-0.26	-0.03	-0.03	-0.01	-0.04	-0.02	0.11	0.02	1.00		
18	*Female*	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	0.04	-0.02	0.00	0.01	0.01	-0.02	-0.01	0.00	-0.05	0.05	1.00	
19	*FromAffectedArea*	-0.04	-0.08	-0.03	-0.07	-0.02	-0.03	-0.02	0.33	-0.05	-0.01	0.01	-0.02	0.04	0.00	-0.02	0.01	0.02	0.01	1.00

Table D.3. Variance inflation factor (VIF) of the independent variables in the regressions using the full dataset

Variable	VIF	1/VIF
Hispanic	1.90	0.53
DJT	1.85	0.54
*Hispanic*DJT*	1.83	0.55
*Hispanic*FEMA*	1.75	0.57
NewsCount (centered)	1.60	0.63
NumCampaigns	1.56	0.64
*Hispanic*NewsCount*	1.33	0.75
FEMA	1.24	0.81
FromAffectedArea	1.14	0.88
StartTime	1.12	0.89
NewEvent	1.11	0.90
ln(Goal)	1.06	0.94
Updates	1.05	0.95
NumWords	1.05	0.95
SocMedia	1.03	0.97
NumVideo	1.02	0.98
FBFriends	1.02	0.98
Female	1.02	0.98
Mean VIF	1.32	

Table D.4. Variance inflation factor (VIF) of the independent variables in the regressions using the subset dataset (Hurricane Maria)

Variable	VIF	1/VIF
NewsCount (centered)	2.59	0.39
NumCampaigns	2.25	0.44
PuertoRican	2.09	0.48
*PR*DJTPositive*	2.02	0.50
*PR*NewsCount*	1.68	0.60
*PR*FEMA*	1.66	0.60
DJTPositive	1.49	0.67
StartTime	1.26	0.80
*PR*DJTNegative*	1.19	0.84
ln(*Goal*)	1.11	0.90
DJTNegative	1.11	0.90
FEMA	1.10	0.91
NumWords	1.06	0.94
Updates	1.06	0.94
SocMedia	1.06	0.95
FromAffectedArea	1.05	0.95
FBFriends	1.03	0.97
NumVideo	1.03	0.97
Female	1.01	0.99
Mean VIF	1.41	