Money to Burn
Crowdfunding Wildfire Recovery[*]

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Abstract

Person-to-person charity has grown substantially in recent years, yet little is known about who benefits from it. This paper uses micro data on crowdfunding campaigns after a major wildfire to ask whether donors give according to the comparative need of beneficiaries. Linking to personal financial data and holding losses fixed, we find that beneficiaries with incomes above $150,000 receive 28% more support than beneficiaries with income below $75,000 and are more likely to have a campaign in the first place. We document that high-income beneficiaries possess several network advantages when soliciting crowdfunding. However, a networks mechanism does not fully explain why donors who give to multiple campaigns tend to give larger amounts to higher-income beneficiaries. These findings suggest that crowdfunded private charity may exacerbate income inequalities in the recovery process.

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1 INTRODUCTION

A central debate in economics is how much to rely on government programs versus individual actions to address societal challenges (Hayek, 1944; Roberts, 1984; Andreoni and Payne, 2003; List, 2011). Natural disasters, which have intensified in recent decades, highlight this trade-off. Government disaster aid programs often fail to direct resources to those in the greatest need (Begley, Gurun, Purnanandam, and Weagley, 2022; Billings, Gallagher, and Ricketts, 2022), leaving a recovery funding gap that *could* be filled by private charity. But, *does* private charity serve this role? There is a genuine empirical tension behind this question. On the one hand, households left out of government loan programs might attract more charity because they have greater need. On the other hand, poorer households may receive less charity because they have fewer social connections relative to wealthier disaster survivors. This paper investigates whether crowdfunded private charity helps the most vulnerable in the context of a major wildfire.

It is increasingly the case that private charity after disasters is transferred directly to individuals through crowdfunding platforms as opposed to indirectly through non-profit organizations (NPOs).[1] In particular, GoFundMe has emerged since 2010 as a way for disaster survivors to quickly raise money from individuals all over the world, extending their funding network beyond close friends and families. In fact, a stated goal of GoFundMe is "...breaking down barriers between those in need and those available to help them" (GoFundMe, 2023). According to the company, between 2013 and 2023, U.S. disaster recovery campaigns on GoFundMe grew from $3 million to over $106 million (Flavelle, 2024). We exploit this setting to understand the allocation of person-to-person charity, assembling a comprehensive sample of the GoFundMe campaigns launched in support of Coloradans whose homes burned in the Marshall Fire on December 30, 2021.

This wildfire was the most costly fire in Colorado history. It destroyed over 1,000 structures and led to $2 billion in damages in a matter of hours. The fire burned a large and economically diverse swath of suburban Boulder County, within commuting distance of Denver and Boulder. The burned properties included single family homes, townhouses, condos, an apartment building, and

[1] For example, according to a Time Magazine article, GoFundMe proceeds have, on occasion, dwarfed donations to Salvation Army relief efforts after disasters (Chan, 2017).

two mobile home parks. The vast majority of affected homeowners were *severely* underinsured, with uncovered expenses averaging $110 per square foot (United Policy Holders, 2023). While rebuilding requires thousands in upfront soft costs (e.g., architectural fees), insurance payouts are held in escrow by mortgage lenders and paid out only as hard costs are invoiced. GoFundMe proceeds, in contrast, provide immediate liquidity and the funds raised proved significant: Within just a few weeks, Marshall Fire GoFundMe campaigns raised $23 million, representing 15% to 26% of the estimated insurance gap. By comparison, the Federal Emergency Management Agency (FEMA) issued grants to individuals amounting to a total of only $2 million. Though large in aggregate, crowdfunded support varies substantially across households: 10% of fire survivors with a GoFundMe campaign received more than $60,000 while 12% raised less than $5,000.

We match individual-level crowdfunding data to the personal credit characteristics, housing characteristics, and rebuilding efforts of disaster survivors. Because we jointly observe what households lost, how much crowdfunding they raised, and households' pre-fire financial condition, we can directly evaluate the allocation of disaster crowdfunding. It is unclear *ex ante* whether GoFundMe campaign proceeds would go disproportionately to the most vulnerable. High income households may have wealthier networks capable of providing more meaningful financial support. If GoFundMe primarily draws from these existing connections via a *personal networks mechanism*, then crowdfunded support would tend to be regressive. Conversely, crowdfunding is a vehicle to solicit support beyond one's close network and the social messaging surrounding GoFundMe campaigns is about helping people in desperate situations. Beneficiaries often describe their financial losses in the campaign text, making "need" imperfectly observable to potential donors. In addition, campaigns are widely shared through school and religious networks as well as on social media and in traditional news, often with a particular focus on the most tragic cases, thus amplifying the campaigns of the most vulnerable. This *social charity mechanism* predicts a negative relation between income and GoFundMe proceeds.

Consistent with a personal networks mechanism, our evidence robustly shows that wealthier households benefit more from crowdfunding than their more financially vulnerable neighbors, even holding constant precisely-measured indicators of real estate losses due to the fire. And, the magnitudes are striking. A household earning more than $150,000 annually can expect roughly 28% more GoFundMe proceeds than a household earning less than $75,000 per year. This effect size translates into nearly $9,000 in additional funding. Similarly, the average prime credit household raises at least 40% ($12,569) more in GoFundMe proceeds than non-prime households. Extensive margin access to this type of crowdfunding is also regressive. High income households are at least 14 percentage points more likely to be beneficiaries of GoFundMe campaigns. Importantly, these findings are not explained by households in better financial conditions losing greater property value due to the fire. In fact, the literature has found wealthier households tend to be better insured, purchasing more homeowners insurance coverage per dollar of asset value (Gropper and Kuhnen, 2023).

Gaps in crowdfunding have real consequences. Using data on the timing of new construction permits and controlling for a vector of household financial characteristics, we find that people with large GoFundMe proceeds ($30k or more) begin rebuilding their homes 4-8 months faster than counterparts with small GoFundMe accounts.[2] GoFundMe proceeds also correlate with comparatively smaller declines in credit scores 12 months after the fire, suggesting that the immediate liquidity provided by GoFundMe helps households to avoid relying on personal credit to recover. Since we cannot control for all of the components of a household's financial condition that could independently affect recovery speeds, this evidence is suggestive and not causal. Nonetheless, it is consistent with GoFundMe playing an important social insurance role. More broadly, these results signal that the regressivity of GoFundMe is not fully offset by other aspects of the safety net, such as government programs or other forms of charity to help those faced with disasters.

Taken together, our analysis suggests that crowdfunded financial support through GoFundMe serves as informal disaster insurance, helping households recover faster from a major disaster. However, crowdfunded assistance appears systematically tilted in favor of households with higher incomes and greater credit access. This inequality in access to social support likely contributes to the slower recoveries of more financially constrained homeowners.

We use donor- and campaign-level data to investigate the mechanisms driving these results. We find that high income households have multiple network advantages over low income households when soliciting crowdfunding. First, high income households are more likely to have campaigns organized on their behalf by friends or co-workers. The prevalence of these "outside advo-

[2] As of this draft, we are not yet able to evaluate households' success in making a full recovery as many houses are still under construction. Moreover, we do not analyze decisions to rebuild versus sell destroyed lots because, for reasons discussed in Section 2.3, only 1.3% of damaged homes sold in the 22 months after the fire.

cates" in the networks of high income beneficiaries is a reason why high income households are more likely to benefit from a GoFundMe campaign in the first place. In addition, we find that high income beneficiaries have more donors ("network breadth"), garnering 6 additional donations per 10% increase in household income – an effect size that is sufficient to explain most of the intensive margin relationship between income and GoFundMe proceeds. Variation in the technological savvy needed to use a crowdfunding platform is unlikely to drive our findings. Instead, high income households appear to have more donors, in part, because their networks extend beyond the local area, lifting the ceiling on the number of possible connections and diversifying connections to areas unaffected by the same disaster.

Finally, we find a secondary but important role for network generosity ("network depth") as a mechanism. Average donation amounts increase by \$1.56 per 10% increase in beneficiary income – an effect size sufficient to explain 40% of the overall relationship between income and GoFundMe proceeds. Remarkably, we find that generosity is regressive even *within* donor: donors who give to multiple campaigns tend to give larger amounts to higher income beneficiaries. This result implies that a personal networks mechanism, in which donors simply give to who they know, cannot fully explain our results. Instead, other mechanisms are necessary to justify why donors give in unequal amounts in a way that correlates with beneficiary income. We discuss a number of well-documented psychological motives that would be consistent with our findings, including the impact of social pressure on charitable giving (DellaVigna, List, and Malmendier, 2012) and the phenomenon that perceptions of the value of money vary by income (Fechner, 1948). We cannot, however, isolate the psychological motives of donors using data focused on the characteristics of beneficiaries and must leave this task to future research.

Our paper makes several notable contributions. First, our study adds a new dimension to the literature on charitable donations. Much of the existing work on charity focuses on donations to NPOs, rather than to individual beneficiaries, and investigates the motives of donors – including altruism (Harbaugh, Mayr, and Burghart, 2007; Andreoni and Payne, 2013) and social pressure (Croson and Shang, 2008; Shang and Croson, 2009; DellaVigna et al., 2012; List and Price, 2012; Edwards and List, 2014) – when giving to one pre-specified NPO. Our focus on variation in person-to-person giving according to the characteristics of beneficiaries is, therefore, distinct in this literature. Moreover, our setting, in which individuals are given free rein to direct charity to other individuals, speaks to the effectiveness of private charity in addressing inequality (Hayek, 1944). Our results indicate that person-to-person crowdfunded disaster aid is not, at least in the confines of our setting, targeted according to need.

Second, our research provides a novel perspective on the influence of financial technology (FinTech) on households (Olafsson and Pagel, 2017; Gargano and Rossi, 2020; Carlin, Olafsson, and Pagel, 2023; Higgins, 2020). This literature has primarily focused on how FinTech affects household behavior through the presentation of information (Levi and Benartzi, 2020; D'Acunto, Rossi, and Weber, 2023) or priming of behaviors (Kalda, Loos, Previtero, and Hackethal, 2021; Gertler, Higgins, Scott, and Seira, 2023). Another strand of this literature examines household participation and pricing in peer-to-peer lending platforms (Morse, 2015; Hertzberg, Liberman, and Paravisini, 2018). Unlike these papers, our paper highlights the social insurance aspect of crowdfunding. In this light, it is most closely related to Balyuk and Williams (2021), which shows that payments technology (i.e., Zelle) buffers against negative shocks by facilitating person-to-person transfers. In comparison to other payments technologies, crowdfunding is touted as a way of "democratizing" capital access by looking beyond financial institutions as well as close friends and family for support (Davis and Davis, 2021). Our results suggest, instead, that households have unequal access to the social support inherent in crowdfunding platforms.

This study also adds to growing evidence that natural disasters exacerbate inequality (Hornbeck, 2012; Gallagher and Hartley, 2017; Howell and Elliott, 2018; Ratcliffe, Congdon, Teles, Stanczyk, and Martín, 2020; Rhodes and Besbris, 2022; Gallagher, Billings, and Ricketts, 2023; Collier and Kousky, 2023; Biswas, Hossain, and Zink, 2023; You and Kousky, 2023).[3] Previous research finds that pre-existing financial constraints, coupled with disparities in insurance coverage, are associated with higher post-disaster delinquency rates and less rebuilding. Poorer households are also more exposed to climate risk (Wing, Lehman, Bates, Sampson, Quinn, Smith, Neal, Porter, and Kousky, 2022; Fothergill and Peek, 2004). Meanwhile, Federal disaster loans and grants do not effectively counteract these disparities (Begley et al., 2022; Billings et al., 2022; Collier and Ellis, 2023).

[3] Although several papers explore charitable donations in the context of U.S. natural disasters (Deryugina and Marx, 2021; Schwirplies, 2023; Brown, Harris, and Taylor, 2012), these papers focus, not on the determinants of person-to-person charity, but on giving to non-profit organizations (NPOs) and testing the concept of an altruism budget. They find that unexpected disasters do not crowd out donations to other (non-disaster) causes. An implication for our study is that giving to GoFundMe campaigns is unlikely to be a zero-sum game in which individuals have a fixed budget and feel they cannot give to one campaign because they already gave to other campaigns or NPOs.

Put together, existing research highlights the importance of directing aid toward more vulnerable households. Our findings indicate that crowdfunding is, instead, tilted away from the most vulnerable. This finding is important because homeowners' rebuilding decisions carry welfare consequences. In particular, Fu and Gregory (2019) document large positive rebuilding externalities on nearby neighbors and community amenities. This result is consistent with literature documenting spillovers onto nearby house prices from policies that affect housing investment (Harding, Rosenblatt, and Yao, 2009; Rossi-Hansberg, Sarte, and Owens III, 2010; Campbell, Giglio, and Pathak, 2011; Autor, Palmer, and Pathak, 2014). Our paper contributes to this literature by showcasing the importance of social networks as a source of insurance against disasters. However, our findings are also a bellwether of widening inequality as formal insurance providers pull out of climate exposed regions (Sastry, Sen, and Tenekedjieva, 2023) and are replaced, in part, with crowdfunding.

Finally, the income inequality inherent in GoFundMe complements recent work on disparities in economic connections (Kling, Liebman, and Katz, 2007; Chetty et al., 2022a). Within this literature, a particularly relevant study to ours is Miller and Soo (2021) who employ a randomized housing voucher experiment to find that moving to a better neighborhood leads to higher credit scores and less delinquency. These findings highlight important disparities in household support networks that are linked to neighborhoods. Relative to this work, our findings indicate that inequality in financial support networks by income is pervasive and is not just a feature of a household's neighborhood. Higher income people have broader and deeper networks of financial support than their lower income counterparts, even when they come from the same area and face the same disaster. In this way, our work complements recent calls to better understand the determinants of social connections (Chetty et al., 2022b).

2 Data and Background

This section provides background details on the Marshall Fire and describes the data.

2.1 The Marshall Fire & Crowdfunding

On the morning of December 30, 2021, the Marshall Fire sparked near grasslands in Boulder County. Fueled by unusually dry conditions and wind gusts of over 100 miles per hour, the fire quickly spread to become the most destructive fire in Colorado history. Within hours, the fire reached populated suburban areas of Boulder County – specifically, the fire hit Superior and Louisville, which are suburban towns between the cities of Denver and Boulder. By early morning the following day, the fire was contained, but not before it consumed over 1,000 residences and became a major national news story. Due to the unexpected and rapid spread of the fire, many people lost everything they own. It took a few weeks for homeowners to fully grasp that their insurance would, in most cases, be insufficient to cover rebuilding after the fire.

Marshall Fire survivors garnered a significant outpouring of charity from across the country. Survivors as well as their friends, colleagues, and family members took to GoFundMe to raise funds. All told, there were over 1,000 GoFundMe campaigns for survivors of the Marshall Fire, some of which were posted while the fire was still burning. Although there were some notable fundraising efforts targeted towards groups within the Boulder community (e.g., firefighters), the vast majority of GoFundMe campaigns specified an individual or household beneficiary (975 of them).

GoFundMe was the primary way for people to receive person-to-person charitable support after the Marshall Fire. GoFundMe page links were shared on social media, in newspaper articles and local television stories, and in emails from organizations like schools and workplaces. To illustrate the fact that GoFundMe was the primary vehicle for person-to-person support, consider Figure 1, which is a January 14 email informing the Summit Middle School community about how they can support families affected by the fire. Of the 14 families identified in the email, only one family did not have a GoFundMe URL and asked, instead, to receive funds through Venmo.

Figure 2 presents a plot of the estimated fire perimeter on the night of the fire, together with markers for houses that were later visually determined to be destroyed (red) versus damaged by the fire (yellow). The map highlights one devastated neighborhood in Louisville, CO. Most destroyed properties (red) have a GoFundMe campaign (blue dot) associated with them.[4]

[4] Figure 2 also shows a few GoFundMe campaigns outside of the fire line. Most of these cases are for people who incurred smoke damage, lost the property in their storage unit, lost their car to the fire, incurred medical bills from injuries related to the fire, or need assistance getting a hotel room until they can return home. Finally, the fire line is only Boulder County's initial estimate of the fire's impact. Several houses outside the fire line sustained damage from burning embers.

2.2 Collecting Data on GoFundMe Campaigns

To illustrate the information on GoFundMe, consider Figure 3, which presents an example GoFundMe page established for Bill and Jackie Stephens. From this campaign, we know the name of the beneficiary, the amount raised, the number of donors, who is organizing the campaign, and a detailed textual description that describes why this family is in need. In addition, GoFundMe displays recent donors, including their name (non-anonymous donation is the default) and the amount given, on the main page. It is possible to click through to the donations page to collect information on each of the individual donations, which are individually timestamped. We manually gathered all of this public detail for each GoFundMe campaign linked to the Marshall Fire.

To collect a full list of Marshall Fire GoFundMe campaigns, we first gather the GoFundMe campaigns listed on GoFundMe's "Marshall Fire" landing page. We expand the list with campaigns posted to the local Facebook page ("The 'Oh oh' two seven") and 80027strong.com website (see Figure A.1 for a screenshot).[5] Finally, we augment our list of GoFundMe campaigns with searches for "Marshall + fire," "Boulder + fire," "Superior + fire," and "Louisville + fire" on GoFundMe, manually removing false positives. The resulting data set reflects the most comprehensive picture of Marshall Fire GoFundMe donations possible.

We collected these data a few weeks after the fire, on January 20, 2022, and then refreshed the data in May of 2022. Using timestamps in the donation-level data, Panel (a) of Figure 4 presents the dynamic time pattern of donations. We calculate that 90% of donations were made before January 18th (within 19 days of the fire). In addition, as a result of the heightened attention in the first couple of weeks after the fire, GoFundMe campaigns that were founded early attracted significantly more donations from more donors than campaigns that were started later. We illustrate this phenomenon by plotting, in event time, the average accumulation of donors separately for campaigns started before January 15 versus after in Panel (b) of Figure 4.

For each GoFundMe campaign, we collect the name of the beneficiary, the name of the organizer of the campaign (including information on the organizer's relationship to the beneficiary), the text of the campaign description, and whether the page includes pictures. The textual description helps classify the sophistication level of the campaign organizer using the spelling and

[5] Related to the social charity mechanism, the host of 80027strong.com explicitly sought to help people identify campaigns with the greatest need and those that were overlooked.

grammar error rate, as well as the characteristics of the campaign itself – i.e., whether it is a total loss, whether it mentions underinsurance, children, lost pets, or medical issues. Hence, the campaign text signals to potential donors the degree of financial need, which we codify to the extent possible and control for in our regressions. In addition, we collect donation-level information for every contribution. This includes the amount, the date and time, and the name of the donor. We do not analyze the campaign goal amounts selected by the organizer because campaign organizers will sometimes increase the goal amount once the original goal is achieved, thus complicating the interpretation of amounts raised relative to goals.

We also capture the number of times the GoFundMe campaign URL was shared on Facebook and Twitter using the Chrome Extension BuzzSumo. Collecting social media shares is helpful in two ways. First, social sharing is an outcome of interest since the social media presence of a GoFundMe campaign may vary significantly across households. Second, it is a mechanism of interest. Social media presence is a proxy for technological fluency. More technologically capable beneficiaries and associated social networks can exploit larger social media networks to boost GoFundMe campaign proceeds.

2.3 Linking to Public Records

GoFundMe policies require each campaign organizer to state the beneficiary, their connection to the beneficiary, and how the money would be used. We use this information to geolocate GoFundMe campaigns by hand-matching beneficiary names to names in public records. Specifically, we obtain names and addresses of individuals living in Boulder County using public deeds records for homeowners, augmented with detailed public information on the addresses of homes affected by the fire and with public voter registration information. Our hand-matching procedure allows us to append the full legal name and address to the GoFundMe data set. We obtained a high-quality merge that matches 87% of the beneficiaries listed in GoFundMe campaigns. Figure 2 visually illustrates the quality of our hand matching by showing a strong correlation between property destruction (red boxes) and a matched GoFundMe campaign (blue dots).

Boulder County's website posts comprehensive information on tax assessment values, property characteristics (e.g., square footage, bedrooms, finished basement), property sales, and construction permits. These data provide insight into both the characteristics of the houses and the steps taken to rebuild the house. Boulder County property data can be merged with the GoFundMe data using the address field, which we generated from hand-matching GoFundMe beneficiary names to public records.

Since homeowner's insurance payouts are often inaccessible until reconstruction begins, we conjecture that GoFundMe proceeds can be used to clear the liquidity hurdles needed to initiate the rebuilding process. We do not, however, evaluate whether GoFundMe proceeds relate to decisions to sell properties because too few homes sold in the 22 months after the fire. Specifically, only 1.3% of homes (lots) that incurred fire damage transacted, which is less than the share of undamaged homes that transacted (5.8%). And, surveys or Marshall Fire survivors reveal little intent to sell (United Policy Holders, 2023; Crow, Dickinson, Rumbach, Albright, and DeVoss, 2022). A dearth of sales after the Marshall Fire could reflect a variety of pecuniary and nonpecuniary factors. Anecdotally, we spoke to homeowners who would have preferred to sell but chose to rebuild due to an "insurance lock-in" effect, wherein certain coverage add-ons (debris, trees/plants, building ordinance, land stabilization) can only be used if the home is rebuilt. As of this draft, we suspect but cannot yet test that many homeowners are rebuilding properties to sell them upon completion. Given these factors, we focus on permitting speed rather than home sales as our primary measure of disaster recovery.

2.4 Experian Credit Bureau Data

The Experian data provide a comprehensive picture of a person's credit profile (roughly 2,000 credit attributes) and are comparable to data from Equifax or TransUnion, which have been widely employed in the literature (e.g., see Brown, Cookson, and Heimer 2019, Miller and Soo 2020, and Yannelis and Zhang 2021).[6] Like Cookson, Gilje, and Heimer 2022, we also obtain estimates of individuals' incomes and debt-to-income ratios (DTI). This paper utilizes data from December 31, 2021, which is the day after the fire, and from December 31, 2022, which is a year after the fire.

Through its academic data services arm, Experian works with academics to connect credit bureau data to individuals based on an input file of names and addresses (e.g., see work by Bellon,

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Cookson, Gilje, and Heimer 2021; Miller and Soo 2021, and Fonseca and Wang 2022, who have constructed similar databases). We provided Experian with a list of approximately 45,000 individuals living near the fire line, their legal names, and addresses from public records. Experian found 83% of the individuals in our sample (and 85% of homeowners) as of December 31, 2021. These match rates are comparable to other studies that rely on public data to match with credit bureau information.[7] For this sample of matches, Experian returned the data without name and address, but matched to a linkable study ID we provided to Experian which is stored separately from the identifiable input files we used to construct the initial data.

When evaluating the distributional allocation of GoFundMe proceeds, we use estimated income as our primary measure of financial well-being. This is the key explanatory variable in our analysis.[8] Experian's Income Insight product is based on a proprietary predictive model trained on a sample of credit characteristics matched to Form 1040 income data. Income is, for example, highly correlated with credit limits and types of credit accounts. It is important to emphasize that we interpret Experian's income estimate, not as a precise measure of income *per se*, but as a proxy for the unobserved latent construct of financial well-being. We demonstrate the robustness of our main results using two alternative measures of financial health: credit score and DTI.

2.5 Merging and Key Variables

Our analysis centers on the GoFundMe campaigns that can be linked to an individual or household, explicitly dropping group campaigns from the analysis. Further, we restrict attention to campaigns with non-zero donations. This restriction leaves 975 campaigns. Of the remaining affected properties where we do not observe an associated GoFundMe, we expect that most of the residents in these properties chose not to seek social support. Indeed, in Section 3.1.2, we evaluate which household characteristics predict whether or not there is an associated GoFundMe campaign.

About 14% of beneficiary households have multiple campaigns, started by different friends, co-workers, or family members. Since key variables, like GoFundMe proceeds and property value,

[7] For example, Cookson et al. (2022) report an 80% match rate with public tax records to Experian and Cheng, Severino, and Townsend (2021) report an 87% match rate to public court records to TransUnion data.

[8] Prior research shows that the income impact of disasters is typically small and short-lived (Deryugina, Kawano, and Levitt, 2018; Farrell and Greig, 2018), such that survivors with high-incomes at the time of fire are likely to maintain their high-incomes post-fire.

are most easily interpreted at the household level, in most specifications, we aggregate GoFundMe campaigns to the household level by summing proceeds across campaigns for beneficiary members of the same household and averaging the other GoFundMe-level characteristics to the household level. For example, if a household is the beneficiary of two campaigns, one of which mentions children but the other does not, the variable $mentions\_child$ would equal 0.5. For the credit data, we restrict the sample to adults over the age of 24 (non-dependents) and average credit attributes across adults in the household.

After aggregation, the data consists of 635 households matched to property and credit characteristics. All of our conclusions hold when working with this 635 household sample; however, these households experienced varying degrees of damage, which we cannot directly observe unless the house was completely destroyed. Our final sample is, therefore, restricted to the 474 beneficiary households that own homes (excluding renters) that were completely destroyed, and not just damaged, by the fire. By restricting the sample to the owners of destroyed homes, we can control for the market value of the real estate lost to the fire. To construct this variable, we manually gathered from Zillow.com estimates of the market value of each home as of the date of the fire. Then we multiply this estimate by the portion of the property's taxable value that is attributable to the structure as opposed to the land (according to Boulder County's tax assessor). The resulting variable captures the market value of the destroyed structure and is an important control in regressions relating GoFundMe proceeds to household financial condition.

2.6 Descriptive statistics

Figure 5 presents a histogram of GoFundMe proceeds across households. GoFundMe proceeds are right-skewed. Approximately 10% of households received more than $60,000 in their campaigns. Our interest is in understanding what economic factors drive this large variation in GoFundMe proceeds. These proceeds reflect a significant source of social support. In aggregate, GoFundMe campaigns linked to the Marshall Fire received $25.18 million, and the campaigns with individual or household beneficiaries received $23.15 million.

Figures 6 and 7 present the distributions of income and credit scores for the households in our sample, respectively. We see that 15.4% of the households in the sample have average incomes below $50k and 33.7% have average incomes exceeding $100k. This wide distribution of incomes reflects the fire's path, which destroyed homes across a wide array of neighborhood types from mobile home parks to relatively affluent neighborhoods beside golf courses.

Relative to the income distribution, there is less spread in sample credit scores. The credit score distribution is left skewed, with many near-prime households and few subprime households. Appendix Table A.1 draws a comparison to two other samples − a nationally representative sample and a sample of shale mineral rights owners in Texas, both drawn from Cookson et al. (2022). Relative to either of these samples, the GoFundMe sample we study contains a larger fraction of prime consumers. This observation is consistent with our sample consisting of many new-build homeowners (who qualified for mortgages in the recent past) and with Boulder County being relatively well off − e.g., Boulder County's median household income was $87,000 versus the national average of $68,000 in the 2020 Census. Given the more limited variation in credit scores compared to income, we use credit score as a secondary measure of financial condition.

Turning to the characteristics of GoFundMe campaigns in Table 1a, the average GoFundMe campaign raised $23,744 from 172 donors, only 22% of whom chose to be anonymous. Average donation amounts vary widely across campaigns from $10 to $1,228. In Table 1b, after shifting to the household-level sample and restricting to owners of total loss properties, donations increase such that the average household received $31,422 in aggregate GoFundMe proceeds from 218 donors. The market value (Zestimate) of destroyed homes at the time of the fire ranged from $164,600 to $2.9 million, reflecting the diversity of housing stock impacted by the fire.

To validate that this scale of disaster crowdfunding is not unique to Boulder County, we compare the Marshall Fire of December 2021 to the Maui Fire of August 2023. The two areas were similar in terms of median incomes and above-average construction costs at the time of the fires. The Maui fire burned more homes, yet produced a similar ratio of GoFundMe campaigns to homes burned (approximately 90% in both cases). Although there were many differences between the fires, the average donation amount per campaign is nearly identical, about $23,000 in both cases. These observations suggest that results based on the Marshall Fire may generalize, at least to areas experiencing a similar economic and construction environment at the time of the fire.

2.7 GoFundMe Proceeds in the Context of Disaster Aid

How does crowdfunding compare to other sources of disaster recovery funds? Table 2 compares aggregate GoFundMe proceeds to (a) the amount of underinsurance in the Marshall Fire, (b) the amount of direct individual aid provided by FEMA, (c) the interest subsidy offered through the SBA disaster loan program, and (d) other philanthropic efforts, notably the Community Foundation's Boulder Wildfire Fund.

First, using detailed information on the insurance contracts associated with all Marshall Fire claims, the Colorado Division of Insurance (DOI) estimates that uninsured losses from the Marshall Fire range from $86 million to $155 million, depending on the range of rebuild cost quotes that homeowners had received as of April 2022. Therefore, GoFundMe donations reflect 15% to 26% of aggregate uninsured losses.

Second, FEMA provides grants to individuals to fund temporary housing and restore property. However, these grants are typically small. In the case of the Marshall Fire, individual grants amounted to just over $2 million in aggregate (FEMA, 2022). From OpenFEMA data, we estimate that homeowners with FEMA-confirmed property damage received just $2,564 on average.

Third, SBA "disaster loans" are one of the main policy levers to help people who experience disaster losses. Unlike GoFundMe proceeds, households must qualify for SBA loans and, importantly, these loans must be paid back. Nonetheless, an approved SBA loan is valuable because it is given at preferential rates. SBA has two possible rates on disaster loans: a lower rate for people who do not have "credit available elsewhere" (1.438%, in the case of the Marshall Fire), and a higher but still preferential rate (2.875%) otherwise. These rates are substantially below the rates Marshall Fire survivors could receive in private markets, which were at 5% or above in early-to-mid 2022.

In response to a FOIA request, the SBA provided us with a file containing the details of all approved loans without names or addresses (preventing linking). The data do, however, provide us with the amount, application date, approval date, and interest rate for all disaster loans linked to the fire. There were 694 approved SBA loans amounting to $97.34 million in lending under the program. Of these, 264 loans were for exactly $240,000, which is the maximum allowable loan under the disaster loan program. To compare SBA disaster loans, which must be paid back, to GoFundMe proceeds, which do not, we calculate the interest savings (relative to an assumed private credit rate of 5%, the prevailing mortgage rate for prime borrowers at the time) on the first five years of payments for approved loans. Using a standard mortgage calculator, we calculate that households receiving loans at 1.438% (2.875%) can expect to pay $28,020 ($17,580) less in payments over the first five years of a 30-year fixed rate $240k loan. Aggregated over the 264 approved $240k loans, the interest benefit (i.e., the reduction in loan payments over the first five years of the loan) amounts to $5.2 million. Applied to the full set of approved loans, we expect the interest benefit to be roughly $8 million. Thus, the economic value of GoFundMe campaigns is roughly three times the implicit subsidy from SBA disaster loans.

Fourth, people could rely on other sources of charitable support, most notably the Community Foundation's Boulder Wildfire Fund. This fund raised $43.3 million from roughly 80,000 donors (Drugan, 2023). However, only half of the fund has been committed to be spent as of July 2023, and the funds are limited to $20,000 for any household, with more allocated to low-income households with children and other needs. By contrast, GoFundMe's $23.2 million was immediately available to households to use how they wished. In this respect, the most comparable number from the Boulder Wildfire Fund is that about $10 million was spent in the first 90 days after the fire. Relative to this comparison, GoFundMe's support is slightly more than twice as meaningful for survivors in the immediate aftermath of the fire.

In a similar vein, GoFundMe support to households is large in comparison to donations to the roughly 150 "group fundraisers" on GoFundMe for Marshall Fire survivors. In aggregate, these group fundraisers raised about $2 million. Hence, the financial impact of these group campaigns is one-tenth of the GoFundMe campaigns that name individual or household beneficiaries.[9]

These facts highlight that GoFundMe is a major source of disaster recovery funding. While several studies analyze the allocation of formal insurance, FEMA grants, and SBA loans in the context of natural disasters, the role of person-to-person crowdfunding has been largely overlooked. Moreover, unlike insurance payouts for mortgaged homes, GoFundMe proceeds can be accessed immediately, potentially reducing liquidity constraints in the rebuilding process.

[9]The wide gap between individual GoFundMe donations and group fundraisers is particularly notable given that GoFundMe donations to individual GoFundMe's are considered "personal gifts," and thus, are not tax deductible.

3 RESULTS

This section presents our main findings. These results inform *who* has access to disaster crowdfunding and relate GoFundMe proceeds to subsequent real outcomes. In Section 4, we delve into the mechanisms regarding *why* higher-income beneficiaries receive more crowdfunding.

3.1 GOFUNDME PROCEEDS

We begin with graphical evidence on the allocation of private charity directed to households through GoFundMe. Figure 8, Panel (a), uses the full sample of households and shows a significant positive relation between average GoFundMe proceeds and bins of income. One possible reason for the positive association between GoFundMe proceeds and income is that higher income households may have suffered larger fire losses. To account for this possibility, Panel (b) restricts the sample to homeowners who incurred a total loss and plots GoFundMe proceeds as a percentage of the market value of the destroyed structure.[10] Even accounting for the size of the loss in this way, we observe that GoFundMe proceeds trend upward in the income of the household. Importantly, as a share of *uninsured* losses, these graphs almost certainly understate the true slope of the trend. It has been shown in a variety of contexts, including homeowners insurance, that wealthier households purchase more insurance per dollar of asset value (Gropper and Kuhnen, 2023; Armantier, Foncel, and Treich, 2023).

To test the connection between disaster crowdfunding and household financial condition, we estimate the following specification on our household-level sample of homeowners of total loss properties:

$$\log(\text{GFM}_i) = \beta_0 + \beta_1 \cdot f(\text{Income}_i) + \mathbf{X}_i \cdot \theta + \mathbf{C}_i \cdot \zeta + \varepsilon_i \tag{1}$$

where the dependent variable is the natural log of household i's aggregate GoFundMe proceeds. On the right-hand side is our main measure of household financial condition, $Income_i$. The notation $f(\text{Income}_i)$ indicates that we employ different specifications – e.g., log and sets of indicator variables. When we employ the log functional form, the coefficient β_1 is the income elasticity of GoFundMe proceeds. We will also test the link between GoFundMe proceeds and two alternative

[10] We estimate the market value of the structure at the time of the fire by multiplying the Zestimate by the ratio of the taxable structure value to the taxable property value. Section 2.5 describes this estimation in more detail.

measures of household financial condition: credit scores and debt-to-income ratios (DTI).

Important characteristics of the property and household are accounted for in $\mathbf{X}_i$. Most notably, we control for the estimated market value of the structure lost to the fire. We verify that our results are robust to an alternative specification that employs hedonic house-type fixed effects (e.g., counts of bedrooms, counts of bathrooms, and an indicator of a finished basement) in conjunction with a control for the finished square footage of the home. Finally, to account for the fact that donors may give in proportion to the number of owners affected, we also control for the number of adults in the household in $\mathbf{X}_i$.

In designated specifications, we control for a vector of the content of the GoFundMe page, $\mathbf{C}_i$, including whether the description mentions a total loss, children, lost pets, medical issues, underinsurance, as well as the log of the number of words in the description, the error rate according to Grammarly.com (a proxy for writing sophistication), and an indicator for whether the GoFundMe page displays a picture. We employ robust standard errors.

Table 3 presents the results from estimating equation (1) with increasingly rich control variables. Across specifications, the income elasticity of GoFundMe proceeds is between $0.271-0.467$, such that a 10% higher household income is associated with receiving 2.7%−4.7% more in crowd-funded social support. Relative to the sample mean of GoFundMe proceeds ($31,422), this effect size translates to at least $848 in additional proceeds per 10% increase in income. This positive elasticity is statistically different from zero at the 1% or 5% level in all specifications. Column 2 demonstrates that controlling for the market value of the destroyed real estate does not dampen the connection between income and GoFundMe proceeds. This fact is further confirmed in Appendix Table A.2 where we absorb property losses using hedonic features of the home.

Column 4 includes controls for characteristics of the campaign, including proxies for the clarity of the writing, mentions of a total loss, underinsurance, etc.. Controlling for these factors reduces the estimated income elasticity, however, the relationship remains substantial. Interestingly, very few narrative characteristics of GoFundMe campaigns matter for fundraising totals. However, mentions of children and the presence of a picture are important, holding constant other characteristics.

3.1.1 Nonlinearity and Robustness

Next, we estimate specification (1) but replace *log income* on the RHS with a set of categorical variables for different income, credit score, and DTI levels. All regressions include the full array of property and campaign controls originally employed in Column 4 of Table 3.

Table 4 presents the results. We estimate monotonically increasing coefficients on income in Column 2. Households with incomes of \$75k−\$150k have 20% larger GoFundMe proceeds, on average, than households earning less than \$75k. For households with incomes above \$150k, the amount of crowdfunded social support is 28% larger, on average. This latter effect size equates to \$8,798 of mean GoFundMe proceeds across sample households (\$31,422 per the summary statistics in Table 1). The magnitude of these estimates are particularly striking given that there was a concerted push to market the campaigns of households in greater need (e.g., see the commentary by the host of 80027strong.com in Figure A.1).

Despite the limited variation in credit scores in our sample, we detect a positive relationship in Columns 3 and 4. The average prime and super-prime household raise at least 40% (\$12,569) more in GoFundMe proceeds than near- or sub-prime households. Due to sparse data on non-prime consumers, we do not attempt to differentiate non-prime groups. This basic result holds, even after controlling for income in Column 4, highlighting two facts: (a) there is additional financial information contained in credit score that is orthogonal to income (and vice versa), and (b) better access to credit is associated with receiving more crowdfunding. This latter finding complements research linking credit access and social networks, much of which has taken place in developing market contexts (Udry, 1994; Ambrus, Mobius, and Szeidl, 2014; Ambrus, Gao, and Milán, 2022; Carpio, Keller, and Tomarchio, 2022).

Column 5 shows a similar dynamic when DTI is the explanatory variable. Households that enter the fire with lower debt balances, conditional on income, raise more funds through GoFundMe compared to severely debt-burdened households.[11] In other words, this is not a phenomenon in which donors target their donations according to liquidity-constraints, donating more to households that are liquidity-constrained due to large debt payments despite having high-incomes – a.k.a., the "wealthy-hand-to-mouth" households of Kaplan, Violante, and Weidner

[11] We divide DTI at 28% since mortgage lenders provide better terms when mortgage debt would amount to less than 28% of income (Murphy, 2023).

(2014).

3.1.2 Selection into GoFundMe

Thus far, our results speak only to the intensive margin allocation of GoFundMe proceeds. However, households may differ in their likelihood of benefiting from a GoFundMe campaign in the first place. For example, if high-income households are less likely to be GoFundMe beneficiaries, the positive connection between income would overstate the disparity in crowdfunded support between high- and low-income individuals.

To shed light on the determinants of having a GoFundMe campaign, we expand our sample to include all 992 households that own destroyed properties and could be matched to Experian data. Then, we estimate the following linear probability model:

$$\text{Has GFM}_i = \beta_0 + \beta_1 \cdot f(\text{Income}_i) + \mathbf{X}_i \cdot \theta + \varepsilon_i \tag{2}$$

where the dependent variable is an indicator variable for whether the household is a beneficiary of a GoFundMe campaign. We control for the market value of the structure at the time of the fire and the number of adults in the household ($\mathbf{X}_i$). Given our interest in the extensive margin of whether a GoFundMe campaign exists, we do not control for campaign characteristics in this specification.

Table 5, Columns 1-3, present the results from estimating equation (2). In contrast to the idea that high-income people might avoid using GoFundMe for support, we find that households with 10% higher-income are about 2 p.p. *more likely* to have a GoFundMe. According to Column 3, relative to households earning less than \$75k, households with incomes of \$75k−\$150k or over \$150k have 13.6 p.p. or 22.6 p.p., respectively, higher probability of having a GoFundMe. These estimates are highly statistically significant.

This result and the associated effect sizes beg the question of whether high-income households are also more likely to be among the approximately 14% of beneficiary households with multiple campaigns. Columns 4-6 answer this question by restricting the sample to only beneficiary households. Conditional on having one GoFundMe, high-income households are no more or less likely to have multiple campaigns.

In summary, these results suggest that crowdfunded support is regressive not just on the intensive margin but also on the extensive margin.

3.2 Fire Recovery: Reconstruction and Credit

In this section, we examine how receiving larger amounts from GoFundMe relates to subsequent recovery outcomes, focusing on construction permits and credit scores. In interpreting the results in this section, it is important to emphasize that, despite controlling for a wide array of financial and property characteristics, we cannot observe all of the resources (e.g., 401k withdrawals) available to households to recover. Therefore, we cannot say definitively whether GoFundMe proceeds causally affect recovery outcomes.

3.2.1 Construction Permits

Given that the rebuilding of destroyed properties can take years, we use the filing of new construction permits as a leading indicator of recovery from the Marshall Fire. As a preview to the regression evidence, Figure 9, Panel (a), visually demonstrates that more crowdfunding is associated with faster recovery from the Marshall Fire as indicated by a higher probability of filing a construction permit within 18 months of the fire.

To formally link the amount of GoFundMe proceeds to permitting outcomes, we estimate the following specification:

$$Filed\,Permit_i^k = \beta_0 + \beta_1 \cdot f(\mathrm{GFM}_i) + \mathbf{X}_i \cdot \theta + \mathbf{F}_i \cdot \lambda + \varepsilon_i \tag{3}$$

where $Filed\,Permit_i^k$ is an indicator that household i filed for a construction permit within a k months after the fire. We multiply the dependent variable by 100 to ease interpretation. The explanatory variables of interest in these specifications are extensive and intensive margin measures of GoFundMe proceeds, denoted as GFM_i. In addition to controlling for the market value of the destroyed structure and the number of adults in the household ($\mathbf{X}_i$), we attempt to absorb as much of the financial condition of the household as possible in the vector $\mathbf{F}_i$ – including income, credit score, DTI, mortgage balance, and the market value of the land (which can be tapped to secure loans). These are all financial factors that may correlate with GoFundMe proceeds and also independently affect the speed of recovery.

Table 6 presents the results of estimating equation (3). Panel (a) deploys the full sample of households with a destroyed property and asks whether those with a GoFundMe campaign were more or less likely to file a permit by certain dates. The associated y-means (at the bottom of the table) tell us that just 16% of the households owning destroyed properties had filed for a permit as of 12 months after the fire. Nonetheless, the estimate in Column 1 indicates that GoFundMe beneficiaries were 31% (5.2 p.p.) more likely to have initiated reconstruction in that window. By 22 months post-fire, the majority of households (61%) had filed for a permit and, as such, households with GoFundMe campaigns were only 13% (8.1 p.p.) more likely to have initiated reconstruction. We interpret these estimates as evidence that GoFundMe campaigns are associated with faster rebuilding.

Of course, households that start a GoFundMe may be more eager to rebuild. This could happen, for example, if their insurance policies carry shorter rental assistance time limits. These kind of unobserved factors could drive the results in Panel (a). Therefore, in Panel (b), we restrict the sample to households with at least one GoFundMe campaign and ask whether the sums raised correlate with rebuilding speeds. We detect such a relationship after 14 months. According to Column 4, really large GFM amounts, of over \$60k, are associated with filing for permits within 14 months. By contrast, more moderate amounts of \$30k are sufficient to file for permits within 18 months (Columns 5-6). Twenty-two months after the fire, the relationship between permitting and GoFundMe proceeds dissipates as all but the smallest GoFundMe campaigns (those raising less than \$5k) are associated with permits. These results suggest that households with large GoFundMe proceeds begin rebuilding 4-8 months before households with small GoFundMe proceeds, controlling for other differences in their finances.

Despite evidence that GoFundMe campaigns were both extensively and intensively associated with faster rebuilding after the Marshall Fire, it is noteworthy that the majority of homeowners with GoFundMe campaigns still took over 18 months to file construction permits. This delay is surprising given survey evidence indicating that the vast majority of affected homeowners intended to rebuild rather than sell (Crow et al., 2022). And, according to county deeds data, only 1.3% of the homes that incurred fire damage had been sold as of 22 months after the fire. One explanation for the delay in permitting is that wildfire recovery requires many intermediate steps

– e.g., hiring an architect as well as consultants to advise on structural engineering, soil, electrical, and other issues, demolishing and removing debris from the lot, filing for Federal grants and loans, and filing insurance claims. Many of these steps demand large upfront expenditures. Meanwhile, a homeowner's insurance payout is often inaccessible until reconstruction begins (it is held in escrow by the mortgage lender and paid out only as hard costs are invoiced). In a United Policyholders survey captured a year after the fire, nearly half of respondents who had not yet filed for a permit attributed their delay to a lack of funds needed to initiate rebuilding (United Policy Holders, 2023). GoFundMe proceeds, in contrast, provide immediate liquidity to cover soft costs, which may explain why GoFundMe campaigns are positively correlated with rebuilding speeds.

3.2.2 Credit Scores

Additional financial liquidity from GoFundMe may prove pivotal in avoiding adverse credit outcomes, such as maxing out credit cards, taking out new loans, and falling behind on payments. To account for all of these possibilities parsimoniously, we study changes in credit scores after the fire. Figure 9, Panel (b), shows that owners of destroyed properties experienced substantial declines in credit scores over the 12 months after the fire. However, these declines are disproportionately among households with little in GoFundMe proceeds. In contrast, large GoFundMe proceeds, of $30k or more, are associated with negligible changes in credit scores.

More formally, in Table 7, we control for the same financial and property factors as in equation (3), including credit score at the time of the fire, but change the dependent variable to be the household's credit score 12 months after the fire. Households that received more crowdfunding had comparatively higher credit scores 12 months after the fire. According to Column 2, 10% more in GoFundMe proceeds is associated with a credit score that is a quarter of a point higher, on average. In Column 3, we observe that most of this impact is driven by relatively modest GoFundMe proceeds. In particular, compared to households that receive $5k or less from GoFundMe, households that receive over $5k have credit scores that are 14 points higher a year after the fire. There is no additional impact on credit scores from receiving larger amounts of crowdfunding. One interpretation is that reductions in credit scores are due to running through one's liquid savings buffer and GoFundMe offers replenishment. As observed in Lusardi, Schneider, and Tufano (2011) and Kaplan et al. (2014), many households have few liquid assets.

In summary, there is an association between GoFundMe proceeds and recovery outcomes. While it is true that unobserved sources of financial support may correlate with both GoFundMe proceeds and speed of recovery, the fact that GoFundMe remains important after controlling for observable household financial characteristics is suggestive evidence that GoFundMe campaigns affect recovery outcomes. Moreover, the fact that it takes GoFundMe proceeds over certain amounts to significantly affect outcomes – e.g., at least $5k for credit score benefits and $30k for faster permits (within 18 months) – supports a causal interpretation.

4 MECHANISMS

The previous section established that disaster crowdfunding is regressive in allocation. This section explores why.

4.1 NETWORK ADVANTAGES

One explanation is that higher-income households have access to different types of networks than lower-income households, leading to differences in GoFundMe proceeds. We explore the role of network size ("breadth") and generosity ("depth") in this subsection.

4.1.1 NETWORK BREADTH

To evaluate whether high-income households have broader networks, we set the dependent variable to equal the logged number of donations and re-estimate Equation (1) with the same controls. Table 8 presents the results. Income is positively and highly significantly related to the number of donations to a GoFundMe campaign (Columns 1−5). This result holds conditional on the extent of property loss and variation in GoFundMe campaign features. Specifically, a 10% higher-income is associated with 2.4%−3.3% more individual donations, representing about 6 additional donations relative to the mean of 218 donations. Assuming these 6 donors each give the average donation amount ($156), a network breadth mechanism could fully explain the $848 increase in GoFundMe proceeds per 10% increase in income that we estimated in Table 3. Hence, a broader network is a key reason for why people with higher-incomes receive more total GoFundMe proceeds.

4.1.2 Network technological capability

Why might high-income households have a broader base of donors? One theory is that high-income beneficiaries have networks that are more technologically capable of using a crowdfunding platform as a payment vehicle, in turn, leading to larger donor numbers to their campaigns. The literature on technological inequalities supports this as a possible explanation (Tucker, 2023).[12] Moreover, our extensive margin result that income predicts having a GoFundMe campaign is consistent with the hypothesis that higher-income people (and their campaign organizers) have greater technological access and know-how.

We test this mechanism by incorporating proxies for network technological capability – namely, the number of times the campaign is shared on social media and the age of the beneficiary. As expected, Columns 4−5 of Table 8 validate that social media sharing is significantly positively related to the number of donors, and the relationship is markedly stronger for Facebook sharing. Beyond indicating a direct role for social networks, this result emphasizes that networks that reach friends of friends (Facebook) are more effective fundraisers than networks that have more impersonal reach (Twitter). The implication is that social proximity matters for the impact of social media on household decisions – a finding that is novel in the literature on the real consequences of social media (Levy, 2021; Müller and Schwarz, 2022; Cookson, Niessner, and Schiller, 2023; Cookson, Fox, Gil-Bazo, Imbet, and Schiller, 2023).

Importantly, however, the results in columns 4-5 cast doubt on the theory that the regressive nature of GoFundMe proceeds can be explained by differential technological capabilities. The income elasticity estimate only strengthens with controls for social media sharing of the campaign (Column 3 versus Column 4). The income elasticity estimate is similar even after controlling for beneficiary average age in Column 5. The fact that higher-income people still receive a large number of donations conditional on these proxies, suggests that technological capability is unlikely to explain the regressive distribution of GoFundMe proceeds.

As additional evidence, Columns 6−7 of Table 8 set the dependent variable to social media shares instead of the number of donors. Inconsistent with a *tech-savvy networks* mechanism, the

[12] According to Tucker (2023), financially constrained people have smaller digital footprints because the ability to build an internet data trail – i.e., by owning a smartphone, using a computer, making payments online – reflects economic privilege.

coefficients on income suggest that the campaigns of higher-income beneficiaries get shared *less* over social media.

4.1.3 Network depth

Network advantages may also stem from a wealthier or more generous network, leading to larger average donation sizes. To test the role of network depth, we replace the dependent variable with logged average donation size and re-estimate equation (1) with the same controls.

The results in Table 9 signal that income is positively and significantly related to depth of the GoFundMe campaign. Specifically, a 10% higher-income yields about 1% more in average donation amounts. This effect size translates to an additional $1.56 relative to the mean of average donations across households ($156) shown in Table 1. Multiplying $1.56 by the mean number of donations (218), yields an additional $340 in GoFundMe proceeds per 10% increase in household income. In other words, network depth explains about 40% of the $848 increase in GoFundMe proceeds per 10% increase in income that we estimated in Table 3.

As further evidence that the regressivity in GoFundMe proceeds is not simply driven by inequities in technological capability, the coefficients on social media shares in Column 4 are insignificant, thus, social media sharing does not explain why the average donation amount is higher for higher-income beneficiaries. Finally, we validate that a small number of very large donations are not driving the relationship between income and average donation size. The income elasticity estimates in Columns 5 and 6 are similar when the dependent variable is set to the median or modal donation instead of the average.

We conclude that higher-income beneficiaries received more in crowdfunding after the Marshall Fire, not just because they have broader networks, but because their donors give in larger amounts. The economic magnitudes of the estimates suggest, however, that network breadth likely dominates network depth in terms of explaining a greater portion of the overall relationship between income and GoFundMe proceeds.

4.1.4 Network advocates

The strength of a social network can also be evaluated by observing who solicits funds on the beneficiary's behalf. In this section, we provide direct evidence of who advocates for GoFundMe beneficiaries by studying the relationship of the organizer to the beneficiary, which we code into family (including self), friend, or coworker. Presumably, having a campaign organizer who is outside of the family is a signal of a broader social network.

The estimates in Table 10 speak to whether the advocacy of a non-family organizer varies by income. The test uses a linear probability model version of equation (1) where the dependent variable is an indicator that takes a value of 1 if the organizer is non-family. We robustly find that campaigns belonging to higher-income households are more likely to have been initiated by non-family members. Specifically, a 10% higher-income is associated with 1 p.p. higher likelihood of receiving crowdfunding that was solicited by a non-family member (Column 3). Columns 4 and 5 signal that most of this effect comes from organizers who are friends as opposed to coworkers.

The presence of outside advocates implies the potential for more than one GoFundMe campaign. A household with multiple campaigns may benefit from "omnichannel" soliciting through distinct networks (e.g., coworkers, religious groups, friends). We test this hypothesis in Table 5 (Columns 4-6) and find that higher-income households are not more likely to have multiple campaigns. Thus, while outside advocates may increase the odds of a high-income beneficiary having one campaign, they do not increase the odds of having multiple campaigns.

A related explanation for the larger GoFundMe proceeds of high-income beneficiaries is that outside advocates might be more effective fundraisers. As agents for their beneficiaries, they may be able to solicit funds more forcefully. We test this hypothesis in two ways in Appendix Table A.3. First, we use our main household-level sample and test the impact of having an outside advocate on GoFundMe proceeds. Second, we employ our campaign-level dataset, restricting the sample to households with more than one campaign, holding fixed the household, and testing for a differential fundraising effect by organizer type. The results all suggest that campaigns with non-family organizers do not raise more funds.

In conclusion, an indicator of a strong social network is the presence of an outside advocate who is willing to set up a campaign on behalf of a beneficiary. Higher-income households are more likely to have campaigns initiated on their behalf by friends and co-workers. This factor likely contributes to our extensive margin finding that higher-income disaster survivors are more likely to have a GoFundMe campaign in the first place. Conditional on having a campaign, however, income is not associated with having multiple campaigns and campaigns started by outside advocates do not raise more money conditional on beneficiary income. Hence, the presence of outside advocates is unlikely to explain our intensive margin findings.

4.1.5 Network geographic dispersion

Thus far, our results point to network breadth as the main driver of our intensive margin (GoFundMe proceeds) results. But why would higher-income beneficiary households have broader support networks? One possibility is that higher-income households may have networks that extend beyond the local area (e.g., due to living in different places for school and work). Network geographic diversity is helpful, not just because it boosts the ceiling on the number of possible connections, but also because diverse connections are less likely to be affected by the same disaster.

To explore this idea, we classify every donor in the donation-level data according to whether that donor is linked to the local area or not.[13] Using this classification, we calculate the percentage of donors that are non-local by GoFundMe campaign. Finally, after aggregating to the household level, we test whether the non-local share of donors to a household's campaign(s) (the dependent variable) correlates with the income of the household.

According to the estimates in Table 11, higher-income beneficiaries draw a significantly larger share of their donors from outside of Boulder County. A 10% increase in income is associated with a 0.3 p.p. higher share of donors from outside the local area. This result is robust to controlling for social media shares as well as age – implying that neither the global connectivity benefits of a larger social media presence nor the time spent forming more distant connections can explain this result. Instead, we interpret our results as evidence that higher-income beneficiaries have more contacts outside of the local area, which is another form of network advantage.

4.2 Donor motives

We have established that the wealthy have numerous network advantages in soliciting funds after a disaster; however, we have not addressed the motives of their donors. Why do donors give

[13] Specifically, a donor is classified as local when the donor's first and last name combination is found in Boulder County's public records. Otherwise, we classify the donor as non-local. We set this indicator to missing for anonymous donors or when the name matches with Boulder County records but the name is too common (e.g., there are multiple people named John Smith in Boulder County) to be confidently classified as local.

to the campaigns of comparatively well-off beneficiaries? In this section, we discuss some of the motives that may govern donation decisions.

4.2.1 Motives: Giving to who you know

A simple explanation for many of our findings is that donors tend to give to the people they know – i.e., a personal networks mechanism. The regressive allocation of GoFundMe proceeds could happen in this case because wealthier people tend to know more people capable of donating and donating larger amounts. Indeed, List and Peysakhovich (2011) documents a positive association between donor wealth and charitable giving in the context of NPOs. This mechanism is also related to homophily effects in the economics literature, under which people from similar socioeconomic backgrounds are more likely to trust one another, in turn, affecting everything from investment decisions to medical provider referrals (Gompers, Mukharlyamov, and Xuan, 2016; Zeltzer, 2020; Li, Zhang, Jiang, and Hu, 2023). An analog in the psychology literature is the "identifiable victim effect" (Galak, Small, and Stephen, 2011; Small, 2015).

Under a *pure* personal networks mechanism, we would expect donors to donate equally to the fire survivors they know – i.e., generosity should be donor-specific rather than related to the characteristics of the beneficiary. If, instead, the same donor gives in different amounts and those amounts correlate with beneficiary income, all else equal, this would suggest other mechanisms are at play. To test this idea, we run the following donation-level specification on names that appear as donors in multiple campaigns:

$$\log(\text{GFM Donation Amt}_{d,i,c}) = \beta_0 + \beta_1 \cdot Log\,Income_i + \mathbf{X}_i \cdot \theta + \mathbf{C}_c \cdot \zeta + D_d + \varepsilon_{d,i,c} \qquad (4)$$

The outcome variable is the donation amount given by donor d to campaign c belonging to beneficiary i (N=20,249). The donation-level data is merged with the income and property information, $\mathbf{X}_i$, of the household beneficiary as well as the campaign characteristics of the associated GoFundMe, $\mathbf{C}_c$. Importantly, equation 4 includes a donor fixed effect, D_d, after limiting the sample to the approximately 11.5% of donors with names appearing as donors in multiple campaigns. This fixed effect ensures that identification comes from variation in donation amounts across campaigns within donor. Standard errors are clustered on beneficiary household.

Results are presented in Table 12. Donor fixed effects absorb much of the variation in donation amounts, as evidenced by the high *R-squared* on these regressions. However, we robustly find that donors give larger amounts to higher-income beneficiaries, suggesting that a portion of the variation in donation amounts is beneficiary-specific. The income elasticity estimates in Columns 1-3 suggest that a donor gives about 0.4% more to beneficiaries with 10% higher-incomes. Relative to the mean donation amount across all donations in this restricted donor sample ($134), this effect size translates to about $0.54. While seemingly small, when aggregated across many donors, this effect can have a substantial impact on total GoFundMe proceeds. For example, from the indicator variables in Column 4, we estimate that beneficiaries with incomes above $150k collect 6% (or $8.71) more, on average, from the same donor compared to beneficiaries with incomes below $75k. Since the average beneficiary household in our sample gets about 218 donations, if all donors gave $8.71 more, the beneficiary would receive $1,899 more in GoFundMe proceeds. Put differently, the tendency for the same donor to give larger amounts to wealthier beneficiaries could explain up to 22% of the additional $8,798 in GoFundMe proceeds received by households earning over $150k as estimated in Table 4. The income elasticity estimates in Table 12 are similar when, in Columns 5-6, we limit the sample to local donors – i.e., donors with names that match Boulder County public name records and are unique (appear only once) within Boulder County.

The surprising fact that the same donor gives larger amounts to richer beneficiaries, suggests that a simplistic "who you know" mechanism, while likely important, is insufficient to fully explain the allocation of donations across GoFundMe campaigns. The rest of this section attempts to parse some of the motives for giving more to higher-income disaster survivors.

4.2.2 Motives: Altruism vs. social pressure

Much of the charity economics literature focuses on identifying the roles of altruism, characterized as the "warm glow" of giving, and social pressure, which is the idea that individuals give under pressure from the solicitor or out of reputational concerns. There is substantial empirical evidence in the context of NPOs supporting both motivations (Soetevent, 2005; Croson and Shang, 2008; Shang and Croson, 2009; DellaVigna et al., 2012; List and Price, 2012; Andreoni and Payne, 2013; Edwards and List, 2014; Smith, Windmeijer, and Wright, 2014; Li and Riyanto, 2017; Sasaki, 2019).

We expect these motives, if present, to appear in the GoFundMe data in different ways. To evaluate the role of altruism, we assume that donors who are primarily motivated by the "warm glow" of giving are more likely to opt out of their name being identified next to their GoFundMe donation (GoFundMe identifies donors by default). Hence, we use the anonymous shares of donation counts as proxies for the extent to which a campaign's donors are motivated by pure altruism. These regressions ask whether higher-income beneficiaries get a comparatively higher or lower share of donations motivated by pure altruism.

We evaluate the role of social pressure in a few ways. First, we assume that the more donors are motivated by social pressure, the more likely they will benchmark their donation against others (Edwards and List, 2014), thus, leading to more herding in donation amounts. As in Smith et al. (2014) and Sasaki (2019), we use the strength of the mode – measured as the faction of donations that equal the mode – as a proxy for the extent of social comparison within the campaign. Second, we assume that social pressure is elevated in a work environment, where people generally know each others' names and see each other daily, and where a reputation for stinginess can have negative consequences.

With these proxies in hand, we use our campaign-level data to test for variation in anonymous and modal donation shares by beneficiary income and by the interaction between income and a dummy for whether the campaign is initiated by a co-worker. If donations to higher-income campaigns are motivated by social pressure rather than pure altruism, we should expect a smaller anonymous share and a greater modal fraction in campaigns with higher-income beneficiaries, particularly when the campaigns are organized by co-workers.

The results, presented in Table 13, do not lend support to either motive as an explanation for the regressivity of GoFundMe proceeds. According to Columns 1-3, higher-income beneficiaries do not receive disproportionate altruistic support, as measured by the anonymous share of donors. Consistent with our expectations, the estimates in Columns 4-6 suggest that work environments are associated with more social benchmarking, as evidenced by a stronger mode when the campaign is organized by a co-worker. However, this symptom of social pressure does not vary by beneficiary income, as indicated by the null interaction term in Column 6.

Although we do not find a clear motive for why the same donor would choose to give more to higher-income beneficiaries, the literature provides two alternative explanations that would fit the results. First, there is the possibility that donors view their charity as a sort of social insurance premium paid to receive support in a future time of need (List, 2011). Individuals who subscribe to this view may give more to higher-income households since these households can give generously in return. A second explanation comes from a branch of the psychology of perception (Fechner, 1948). Similar to the concept of declining marginal utility in economics, "psychophysics" describes the mapping from objective dollars to the psychological perception of money. This mapping is thought to follow a nonlinear function because people believe that, for example, a $100 gift will matter more to someone with an income of $30,000 than it will matter to someone with an income of $300,000. It follows that a donor may give a larger amount to her wealthier friend. Unfortunately, without more detailed information on the beliefs of donors, we cannot test these ideas in our data.

5 Conclusion

As climate change accelerates, more households face the prospect of planning for and recovering from a natural disaster (Bernstein, Gustafson, and Lewis, 2019; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021). Each event further strains government budgets (Liao and Kousky, 2022), forcing households to rely on personal resources to plan for and cope with disasters. This task is made all the more difficult by the fact that large homeowners insurers are withdrawing from the riskiest areas and even entire states (Kousky, 2019; Sastry et al., 2023). While it is clear that crowdfunded private charity is an increasingly important form of informal disaster insurance, there has been little study of who benefits from it.

Conditional on losses, we find that disaster crowdfunding benefits high-income households more than the most vulnerable. Moreover, disparities in crowdfunding appear to correlate with disparities in recovery outcomes, all else equal. Higher-income households garner more private charity due to their broader networks of connections as well as the fact that their donors give more on average. We document several personal network advantages, including having more outside advocates and more non-local donors, that contribute to these findings. However, the fact that the same donor tends to give larger amounts to higher-income beneficiaries suggests that a personal networks mechanism is an incomplete explanation.

An implication of our results is that private charity is unlikely to counteract pre-existing inequalities in recovery prospects across the wealth distribution. Instead, crowdfunded charity may exacerbate the distributional impact of wealth differences in access to Federal disaster loans (Begley et al., 2022; Billings et al., 2022) and in the uptake of formal insurance (Gropper and Kuhnen, 2023). More broadly, to the extent that high-income households benefit disproportionately from technological innovations, like crowdfunding platforms, more inequality may follow. As the literature progresses, we hope to see more research on inequalities in social networks, their causes, and remedies, as well as on the motivations of donors when choosing a disaster aid allocation across households.

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Table 1: Summary statistics

Panel (a) presents campaigns-level summary statistics for all GoFundMe individual fundraisers. Group fundraisers and fundraisers that raised zero dollars are excluded. Fundraisers for beneficiaries excluded from our main analysis sample are included. Panel (b) presents household-level summary statistics using our main analysis sample. For the 14% of households with multiple campaigns, campaign information is summed or averaged across their campaigns, as appropriate. Credit attributes and income are averaged across adults in the household. The household sample is restricted to only those beneficiary households that own their home (renters are excluded) and could be matched with Boulder County property records as well as with Experian credit data. We further exclude the approximately 7% of beneficiary households that did not experience a total loss due to the fire (i.e., incurred only smoke or minor fire damage).

	Mean	St. Dev.	Min	Median	Max	Sum
GFM Proceeds	23,744.49	24,564.53	10.00	16,090.00	297,021.00	23,150,877.00
Num. Donations	171.71	319.59	1.00	117.00	8,947.00	167,420.00
Anonymous Pct. of Donations	0.22	0.11	0.00	0.21	1.00	
Avg. Donation Amt.	144.87	72.15	10.00	134.20	1,227.80	
Obs.	975					

(a) Campaign-level, full sample

	Mean	St. Dev.	Min	Median	Max
GFM Proceeds	31,422.12	28,490.99	200.00	23,874.50	297,021.00
Num. Donations	217.96	433.65	5.00	158.50	8,947.00
Anonymous Pct. of Donations	0.22	0.09	0.00	0.21	0.75
Avg. Donation Amt.	156.42	61.95	35.14	143.86	709.40
Num. GFM Campaigns	1.17	0.48	1	1	5
Has Multiple GFM Campaigns	0.14	0.35	0	0	1
Num. FB + Twitter Shares	56.92	57.38	0.00	44.00	622.00
Mention Underinsurance	0.13	0.34	0.00	0.00	1.00
Mention Total Loss	0.98	0.13	0	1	1
Mention Children	0.46	0.49	0.00	0.00	1.00
Mention Medical Condition	0.04	0.19	0.00	0.00	1.00
Mention Pets	0.06	0.23	0.00	0.00	1.00
Num. Words in Description	182.17	114.87	1.00	153.00	856.00
Num. Errors per Word	0.09	0.70	0.00	0.02	10.00
Has Picture	1.00	0.05	0	1	1
Organizer is Family/Self	0.37	0.47	0.00	0.00	1.00
Organizer is Friend	0.54	0.49	0.00	1.00	1.00
Organizer is Coworker	0.08	0.26	0.00	0.00	1.00
Structure to Taxable Value Ratio	0.58	0.13	0.08	0.56	0.99
Zestimate	951,718.40	394,883.20	164,600	877,050	2,900,000
Num. Adults in Household	1.87	0.82	1	2	7
Income (dollar thousands)	102.67	41.62	32.00	96.25	243.00
Vantage Credit Score	794.56	45.04	608.50	807.00	850.00
DTI	25.50	15.89	0.00	25.00	101.00
Filed Permit wi 18 months	0.46	0.50	0	0	1
Obs.	474				

(b) Household-level, analysis sample

Table 2: GoFundMe relative to uninsured losses and other sources of financial support

This table puts GoFundMe proceeds in the context of uninsured losses, as estimated by the Colorado Division of Insurance. This table also compares the the economic value of SBA loans, FEMA direct support to individuals, and the Boulder Wildfire Fund (which is another major philanthropic effort in support of fire survivors).

Category	Amount ($mm)	Category	Amount ($mm)
Total Loss	1,020.35		
Underinsurance (Colorado DOI)		All SBA Loans (694 loans)	97.34
... rebuild cost $350/sqft	155.00	... implied 5-year interest savings	7.99
... rebuild cost $300 /sqft	86.00		
		Maximum SBA Loans (264 loans)	63.36
GoFundMe		... implied 5-year interest savings	5.20
... all donations	25.18		
... donations to individuals or households	23.15	FEMA Direct Support to Individuals	2.10
Boulder Community Wildfire Fund	43.30		
... spending in first 90 days	10.00		

Table 3: Determinants of GoFundMe proceeds, the role of beneficiary income

This table presents OLS regressions using the specification in equation 1, where the dependent variable is logged GoFundMe proceeds ($). The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. Most specifications control for, Log Mkt. Value of Structure, which is an estimate of the market value of real estate lost to the fire. Appendix Table A.2 offers a version of this table with alternative property loss controls. Column 4 includes a vector of campaign-related controls. For households with multiple campaigns, campaign variables are averaged across campaigns. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log GFM Proceeds			
	(1)	(2)	(3)	(4)
Log Income	0.397***	0.451***	0.467***	0.271**
	(0.103)	(0.106)	(0.104)	(0.107)
Log Mkt. Value of Structure		−0.205**	−0.203**	−0.213**
		(0.102)	(0.102)	(0.092)
# Adults in Household			0.050	0.029
			(0.063)	(0.059)
Mention Underinsurance				−0.087
				(0.138)
Mention Total Loss				0.752
				(0.477)
Mention Children				0.718***
				(0.093)
Mention Medical Condition				0.144
				(0.243)
Mention Pets				0.235
				(0.153)
Log # Words in Description				−0.013
				(0.048)
# Errors per Word				0.075
				(0.055)
Has Picture				0.627***
				(0.085)
Observations	474	474	474	474
R^2	0.028	0.036	0.038	0.185

Table 4: Determinants of GoFundMe proceeds, nonlinearity and robustness

This table presents OLS regressions using the specification in equation 1, where the dependent variable is logged GoFundMe proceeds ($). The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. Column 2 uses indicators for bins of income. Columns 3-5 tests two alternative measures of financial wellbeing: Vantage Credit Score and Debt-to-Income. All regressions control for the market value of real estate lost to the fire, the number of adults in the household, as well as a vector of campaign-related characteristics. For households with multiple campaigns, campaign variables are averaged across campaigns. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log GFM Proceeds				
	(1)	(2)	(3)	(4)	(5)
Log Income	0.271**			0.214**	0.276**
	(0.107)			(0.108)	(0.112)
Income 75k-150k		0.204**			
		(0.099)			
Income >150k		0.282*			
		(0.148)			
Credit Score 700-760			0.398*	0.331	
			(0.235)	(0.238)	
Credit Score >760			0.440**	0.353*	
			(0.183)	(0.185)	
DTI 28-56					0.410**
					(0.206)
DTI <28					0.412**
					(0.208)
Controls	Y	Y	Y	Y	Y
Observations	474	474	474	474	470
R^2	0.185	0.184	0.185	0.192	0.187

Table 5: Selection into having a GoFundMe campaign

This table presents linear probability estimates using the specification in equation 2, where the dependent variables are indicators for whether the household is the beneficiary of a GoFundMe campaign and whether the household has multiple GoFundMe campaigns conditional on having at least one. The data are aggregated to the household level. In Columns 1-3 the sample includes all households that own a destroyed home and could be matched to Experian data. In Columns 4-6, the sample is further restricted to only GoFundMe beneficiaries. The key explanatory variable, average household income, is presented in either log form or as binned indicators. All regressions control for the Log Mkt. Value of Structure, which is an estimate of the market value of real estate lost to the fire, and for the number of adults in the household. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Has a GFM			Has Multiple GFMs		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Income	0.189***	0.211***		−0.003	−0.005	
	(0.035)	(0.036)		(0.038)	(0.037)	
Income 75k-150k			0.136***			0.012
			(0.033)			(0.036)
Income >150k			0.226***			−0.011
			(0.061)			(0.049)
Log Mkt. Value of Structure		−0.130***	−0.117***		0.007	0.008
		(0.035)	(0.035)		(0.040)	(0.040)
# Adults in Household		−0.011**	−0.013**		0.002	0.003
		(0.005)	(0.005)		(0.024)	(0.024)
Observations	992	992	992	474	474	474
R^2	0.026	0.042	0.035	0.00002	0.0001	0.001

Table 6: GoFundMe proceeds and the speed of rebuilding

This table presents linear probability model estimates using the specification in equation 3. The dependent variable is whether a household filed a building permit within 12, 14, 18, or 22 months after the fire. The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. Panel (a) includes all households of destroyed homes in our data and the key explanatory variable is a binary indicator of having a GoFundMe campaign. Panel (b) restricts this sample further to households with a GoFundMe campaign and the explanatory variable of interest is the total amount in GoFundMe proceeds raised by the household, deployed as binned indicators. All columns control for property loss (log market value of the structure), the number of adults in the household, and household financial condition (log income, credit score, DTI, log mortgage balance, log market value of the land). The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Filed Construction Permits			
	12m	14m	18m	22m
	(1)	(2)	(3)	(4)
Has GFM	5.248**	9.219***	10.424***	8.052**
	(2.368)	(2.871)	(3.227)	(3.224)
Y-mean (%)	16	26	41	61
Controls	Y	Y	Y	Y
Observations	989	989	989	989
R^2	0.043	0.062	0.034	0.045

(a) All households of destroyed homes

	Filed Construction Permits							
	wi 12m	wi 12m	wi 14m	wi 14m	wi 18m	wi 18m	wi 22m	wi 22m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GFM Proceeds 5k-10k	−2.450	−2.504	1.764	1.700	7.658	7.654	20.303*	20.359*
	(7.779)	(7.787)	(8.970)	(8.984)	(10.175)	(10.186)	(10.467)	(10.465)
GFM Proceeds 10k-30k	1.535	1.568	5.482	5.521	9.695	9.697	25.505***	25.471***
	(6.860)	(6.871)	(7.562)	(7.578)	(8.550)	(8.560)	(8.891)	(8.882)
GFM Proceeds >=30k	3.749		9.452		17.838**		25.915***	
	(6.891)		(7.619)		(8.584)		(8.888)	
GFM Proceeds 30k-60k		0.587		5.709		17.615**		29.236***
		(7.033)		(7.847)		(8.866)		(9.080)
GFM Proceeds >=60k		11.105		18.159*		18.357*		18.191*
		(8.672)		(9.563)		(10.393)		(10.483)
Y-mean (%)	19	19	31	31	46	46	65	65
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	470	470	470	470	470	470	470	470
R^2	0.080	0.086	0.077	0.084	0.044	0.044	0.040	0.044

(b) Households of destroyed homes with a GFM campaign

Table 7: GoFundMe proceeds and post-fire credit scores

This table presents OLS regressions using the specification in equation 3, where the dependent variable is credit scores 12 months after the fire. The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The explanatory variable of interest is the total amount in GoFundMe proceeds raised by the household – Columns 1-2 study a standardized continuous version while Column 3 employs binned indicators. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Credit Score 12 Months Later		
	(1)	(2)	(3)
Log GFM Proceeds	3.131**	2.452*	
	(1.402)	(1.434)	
GFM Proceeds 5k-10k			14.542**
			(6.789)
GFM Proceeds 10k-30k			13.816**
			(6.075)
GFM Proceeds >=30k			14.470**
			(6.137)
Log Mkt. Value of Structure	2.303	−0.278	0.413
	(3.021)	(3.175)	(3.194)
# Adults in Household	−3.288**	−1.909	−1.673
	(1.552)	(1.600)	(1.600)
Credit Score	0.624***	0.612***	0.605***
	(0.048)	(0.048)	(0.047)
Log Income		7.204	7.677*
		(4.633)	(4.632)
DTI		0.459***	0.445***
		(0.108)	(0.107)
Log Mortgage Bal.		−0.711	−0.655
		(0.480)	(0.472)
Log Mkt. Value of Land		−0.443	−0.699
		(2.324)	(2.243)
Observations	474	470	470
R^2	0.502	0.516	0.522

Table 8: Determinants of the number of GoFundMe donors

This table presents OLS regressions using the specification in equation 1, where the dependent variables are the log number of donations to a household's GoFundMe and the log (+ 1) number of social media (Facebook and Twitter) shares. The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. Columns 3-7 include a vector of campaign-related controls. For households with multiple campaigns, campaign variables are averaged across campaigns. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log GFM Donations (#)					Log 1 + FB+Twit Shares	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Income	0.265***	0.332***	0.168*	0.285***	0.244***	−0.254*	−0.456***
	(0.094)	(0.096)	(0.097)	(0.076)	(0.085)	(0.139)	(0.136)
Log Mkt. Value of Structure		−0.217**	−0.218**	−0.033	−0.031	−0.338***	−0.335**
		(0.098)	(0.090)	(0.073)	(0.076)	(0.126)	(0.129)
# Adults in Household		0.029	0.005	0.010	−0.010	−0.011	−0.084
		(0.060)	(0.055)	(0.040)	(0.042)	(0.072)	(0.075)
Log 1+ FB Shares				0.441***	0.439***		
				(0.040)	(0.043)		
Log 1+ Twit Shares				0.129***	0.115***		
				(0.031)	(0.032)		
Age (z)					−0.089**		−0.188***
					(0.036)		(0.055)
Campaign Controls	N	N	Y	Y	Y	Y	Y
Observations	474	474	474	474	435	474	435
R^2	0.014	0.025	0.167	0.531	0.537	0.136	0.164

Table 9: Determinants of average GoFundMe donation amounts

This table presents OLS regressions using the specification in equation 1, where the main dependent variable is the log of average donation amounts to a household's GoFundMe. Columns 5 and 6 replace the average with logs of the median and modal donation amounts. The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. Columns 3-6 include a vector of campaign-related controls. For households with multiple campaigns, campaign variables are averaged across campaigns. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log Average GFM Donation Amount				Median	Mode
	(1)	(2)	(3)	(4)	(5)	(6)
Log Income	0.133***	0.136***	0.105***	0.104**	0.077**	0.086**
	(0.036)	(0.039)	(0.040)	(0.041)	(0.036)	(0.034)
Log Mkt. Value of Structure		0.012	0.002	−0.006	0.015	−0.002
		(0.036)	(0.036)	(0.036)	(0.035)	(0.031)
# Adults in Household		0.019	0.023	0.023	0.013	−0.004
		(0.020)	(0.021)	(0.020)	(0.019)	(0.019)
Log 1+ FB Shares				−0.005		
				(0.018)		
Log 1+ Twit Shares				−0.024		
				(0.015)		
Campaign Controls	N	N	Y	Y	Y	Y
Observations	474	474	474	474	473	473
R^2	0.027	0.030	0.063	0.071	0.033	0.044

Table 10: Determinants of having a non-family GoFundMe campaign organizers

This table presents linear probability estimates using the specification in equation 3, where the dependent variable indicates that the household is the beneficiary of a GoFundMe campaign organized by someone outside of their family (i.e., a friend or co-worker). The dependent variables in Columns 4 and 5 are indicators that the campaign is organized by a friend (vs. family member) or a coworker (vs. family member), respectively. The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. We do not include campaign-related controls because the outcome is who organized the campaign, not how successful the campaign was at fundraising. For households with multiple campaigns, the dependent variable is averaged across campaigns. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Organizer is...				
	Not-Family			Friend	Coworker
	(1)	(2)	(3)	(4)	(5)
Log Income	0.128**	0.120**	0.109**	0.108*	0.038
	(0.052)	(0.054)	(0.055)	(0.059)	(0.065)
Log Mkt. Value of Structure		0.028	0.026	0.018	0.030
		(0.050)	(0.051)	(0.054)	(0.055)
# Adults in Household			−0.037	−0.035	−0.027
			(0.027)	(0.028)	(0.023)
Observations	474	474	474	425	210
R^2	0.013	0.013	0.017	0.015	0.011

Table 11: Determinants of non-local donor shares

This table presents OLS estimates using the specification in equation 1, where the dependent variable is the percentage of campaign donations that come from non-local donors. Non-local is defined as having a unique name that is not in Boulder County's public records (see Footnote 13 for more detail on this process). The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is the log of average household income. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Non-Local % of Donations				
	(1)	(2)	(3)	(4)	(5)
Log Income	2.713**	2.758**	2.902**	3.325**	3.053**
	(1.353)	(1.388)	(1.408)	(1.427)	(1.452)
Log Mkt. Value of Structure		0.239	0.669	0.960	1.093
		(1.402)	(1.242)	(1.253)	(1.233)
# Adults in Household		0.338	0.425	0.438	0.490
		(0.680)	(0.648)	(0.653)	(0.665)
Log 1+ FB Shares				1.336**	1.621**
				(0.646)	(0.660)
Log 1+ Twit Shares				−0.669	−1.025**
				(0.481)	(0.486)
Age					−0.168***
					(0.059)
Campaign Controls	N	N	Y	Y	Y
Observations	472	472	472	472	433
R^2	0.009	0.009	0.055	0.068	0.121

Table 12: Within-donor giving to different GoFundMe campaigns

This table presents OLS estimates using the specification in equation 4, where the dependent variable is the log of the donation amount given by donor d to campaign c belonging to beneficiary i. The data are at the donation-level and the sample is limited to the approximately 12,102 donors (11.5% of donors) with names appearing as donors in multiple campaigns. All specifications include a donor fixed effect, such that variation comes from across campaigns within donor. All regressions control for campaign characteristics (e.g., does the post mention children being affected). The last two columns limit the sample of donors to those with a name matching Boulder County public records, indicating that the donor is local (see Footnote 13 for more detail on this process). Standard errors clustered on beneficiary household are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log Donation Amount					
	(1)	(2)	(3)	(4)	(5)	(6)
Log Income	0.050***	0.042**	0.038*		0.066**	
	(0.019)	(0.019)	(0.020)		(0.029)	
Income 75k-150k				0.036*		0.063**
				(0.020)		(0.026)
Income >150k				0.063**		0.078*
				(0.028)		(0.042)
Log Mkt. Value of Structure		0.013	0.011	0.008	0.010	0.012
		(0.018)	(0.018)	(0.019)	(0.030)	(0.030)
# Adults in Household		−0.011	−0.004	−0.003	−0.001	0.001
		(0.007)	(0.008)	(0.008)	(0.013)	(0.012)
Donor Restriction	-	-	-	-	Local	Local
Donor F.E.s	Y	Y	Y	Y	Y	Y
Campaign Controls	N	N	Y	Y	Y	Y
Observations	20,249	20,249	20,249	20,249	7,050	7,050
R^2	0.823	0.823	0.824	0.824	0.802	0.802

Table 13: Determinants of the anonymous and modal share of donations to GoFundMe campaigns

This table presents OLS estimates. In Columns 1-3, the dependent variable captures the percentage of campaign donations counts from anonymous donors. In Columns 4-6, the dependent variable is the share of a campaigns donation counts that equal that campaign's modal donation amount. The data are at the campaign-level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variables are the log of average household income and an indicator for whether the campaign is organized by a co-worker (instead of a friend or family). All regressions include a vector of campaign-related controls. The intercept is not shown for brevity. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:					
	Anonymous % of Donations			Modal % of Donations		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Income	−0.326	−0.368	−0.882	0.868	0.822	0.882
	(1.273)	(1.270)	(1.250)	(0.865)	(0.866)	(0.887)
Log Income x Org. is Coworker			4.959			−0.581
			(4.358)			(2.489)
Log Mkt. Value of Structure	0.612	0.587	0.534	−0.279	−0.307	−0.301
	(1.292)	(1.297)	(1.304)	(1.186)	(1.181)	(1.188)
# Adults in Household	−0.501	−0.468	−0.460	0.158	0.195	0.194
	(0.561)	(0.565)	(0.563)	(0.520)	(0.517)	(0.518)
Org. is Coworker		2.337	−20.227		2.552^{**}	5.194
		(1.708)	(19.320)		(1.244)	(11.448)
Campaign Controls	Y	Y	Y	Y	Y	Y
Observations	515	515	515	515	515	515
R^2	0.028	0.033	0.037	0.021	0.030	0.030

Figure 1: Example of information sharing about GoFundMe after the Marshall Fire

From: Supporters of Summit <summit.office@bvsd.org>
Date: January 14, 2022 at 8:14:06 PM MST
To: [redacted]
Subject: Summit Community - Marshall Fire Support
Reply-To: juliana.scott@bvsd.org

Dear Summit Alumni Families,

I hope your family was safe during the recent Marshall Fire. Two Summit teachers and six current Summit families lost their homes. Over sixty current Summit families were evacuated during the fire. Thankfully, the entire Summit community of humans was safe; though many special pets were lost. Even though the fire started very close to Summit, we are so thankful there was no impact to the school campus.

During this tumultuous time we have listened carefully to each student's unique account of experiencing the fire, we have made cards for first responders, we have provided meals, clothing, gift cards, water, support and lots of love on a daily basis. Most importantly we have stood *Summit Strong* for our school community when they need us the most. But there is so much more we can do with your help.

I always tell families that *a Summit education lasts a lifetime* and so do our ties to Summit families. Therefore, we have recently reached out to Summit Alumni Families who have lost their homes and gathered Go Fund Me pages. You will no doubt recognize many names just as I do.

I so often hear that reaching out and connecting with our families gives them the boost they need to keep moving forward! Now it's time for *a financial boost*, so please get ready to swipe your credit card!

Below you will find *Go Fund Me* pages for current Summit Families who lost their homes in the fire.
Please give generously, if you can:

(a) Header of Email to Summit School

Below you will find *Go Fund Me* pages for current Summit Families who lost their homes in the fire.
Please give generously, if you can:

Go Fund Me Pages For Current Summit Families:

- **Austin Family** Go Fund Me (Amy Austin, Summit Music teacher)
- **Engelmann Family** Go Fund Me
- **Haag Family** Go Fund Me
- **Hong Family** Go Fund Me
- **Zhang Family** Go Fund Me

Below you will find Go Fund Me pages for Alumni Summit Families who lost their homes in the fire.
Please give generously, if you can:

Go Fund Me Pages For Summit Alumni Families::

- **Bierkatz Family** Go Fund Me
- **Buckman Family** Go Fund Me
- **Cece Davis Family** Go Fund Me
- **Heuston Family** Go Fund Me
- **Marlin Family** Go Fund Me
- **Logan Family** Go Fund Me
- **Payne Family** Go Fund Me
- **Pearce Family** Go Fund Me
- Fontillas Family Support Option: If providing a financial gift, please use Venmo (@T-S-Fontillas) or Zelle (**tsfontillas@gmail.com**)

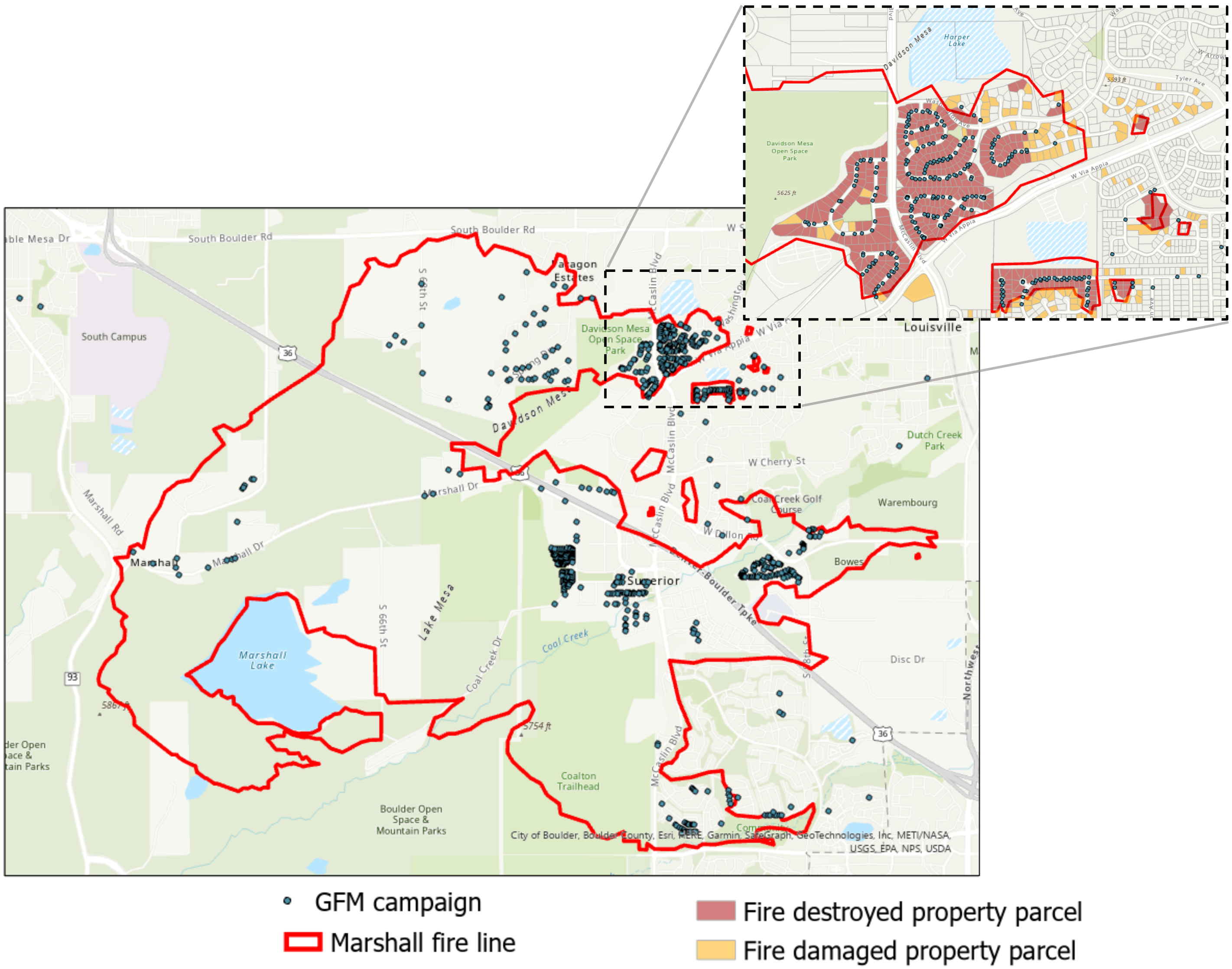
Thank you for your continued support of Summit!

With Much Gratitude,
Adam Galvin

(b) Listing of How to Support Families

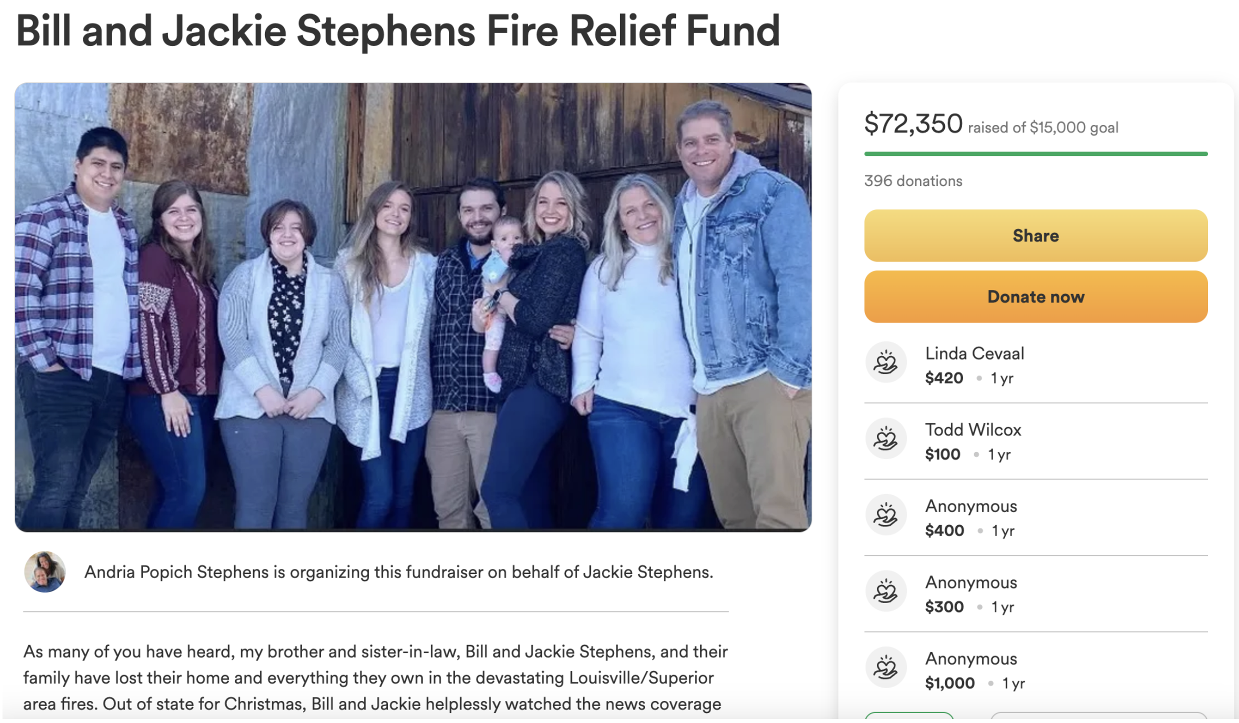
Notes: This figure reports screenshots of two parts of an email to families of students and alumni of Summit Middle School in Boulder. The email is dated January 14, and it lists how to financially support people who lost their homes in the Marshall Fire.

Figure 2: Map of areas affected by the Marshall Fire



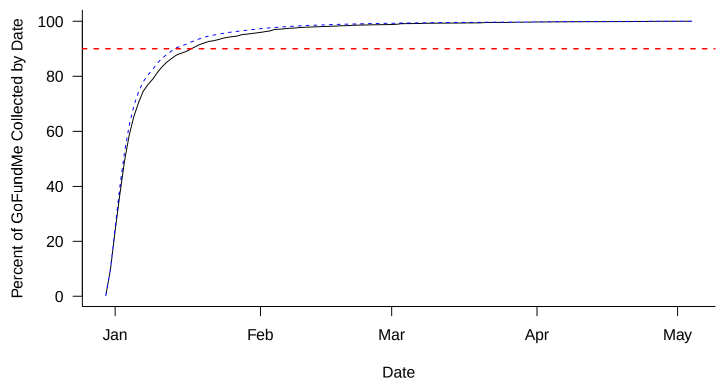
Notes: This figure presents a map of the Marshall Fire's perimeter, destroyed properties (red), fire damaged properties (yellow), and the locations of GFM campaigns. The Marshall Fire sparked around 11 am on December 30, 2021. The zoomed in inset is the Harper fire neighborhood, which conveys the overlap between GFM campaigns and properties affected by the fire.

Figure 3: Example GoFundMe page

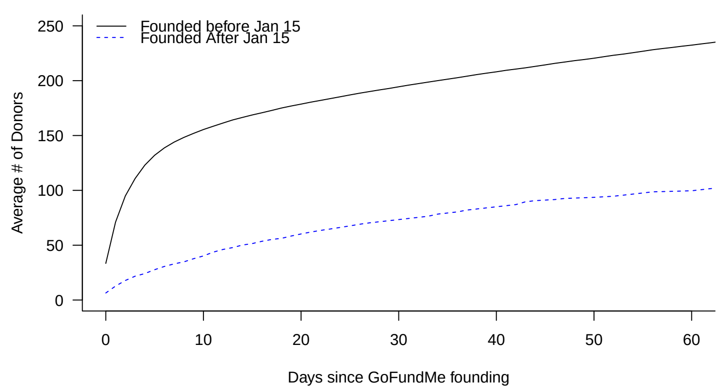


Notes: To illustrate the data available publicly on GoFundMe's website, this figure presents a screenshot of the GoFundMe page established for Bill and Jackie Stephens.

Figure 4: Timing of GoFundMe donations



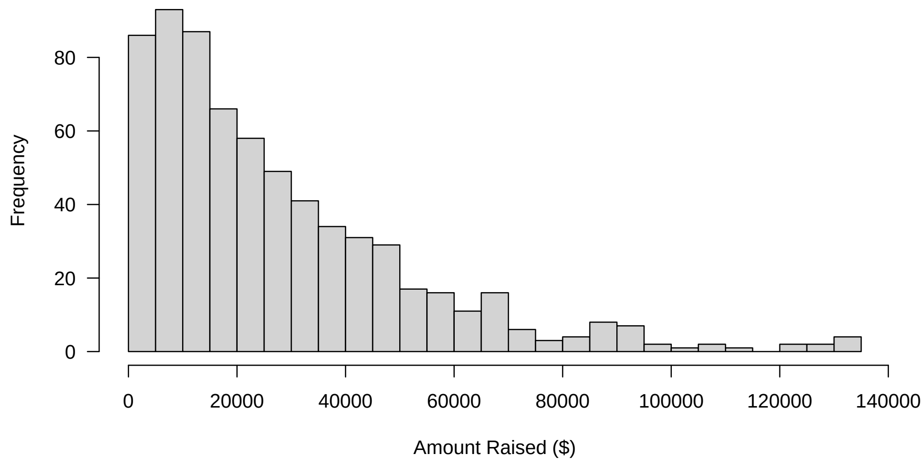
(a) GoFundMe Donations and Donors over Time



(b) Donation Timing: Early versus Late Campaigns

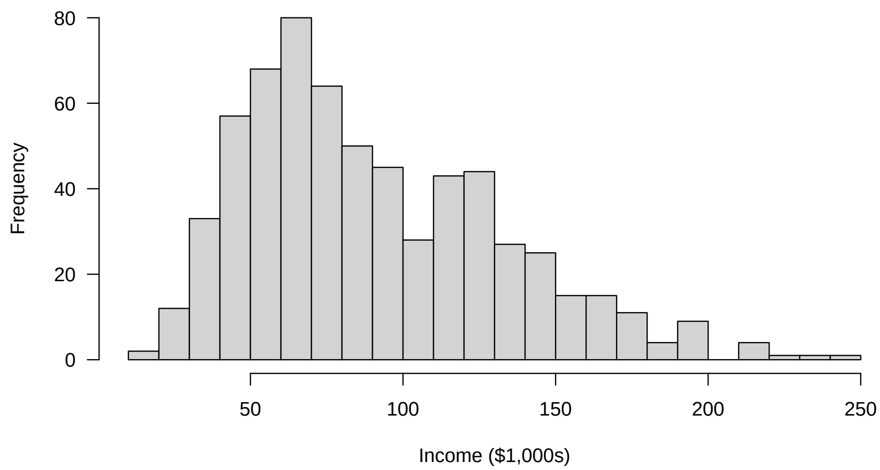
Notes: This figure presents evidence on the timing of donations to GoFundMe campaigns using donation-level data. Panel (a) plots the cumulative fraction of donations (black solid line) and donors (blue dashed line) versus the date of donation. For reference, a red dashed line is placed at 90%. Panel (b) compares the average accumulation of donors in event time (days since GoFundMe founded), split by campaigns that were started before January 15 (early) versus after (late).

Figure 5: Histogram of GoFundMe Proceeds



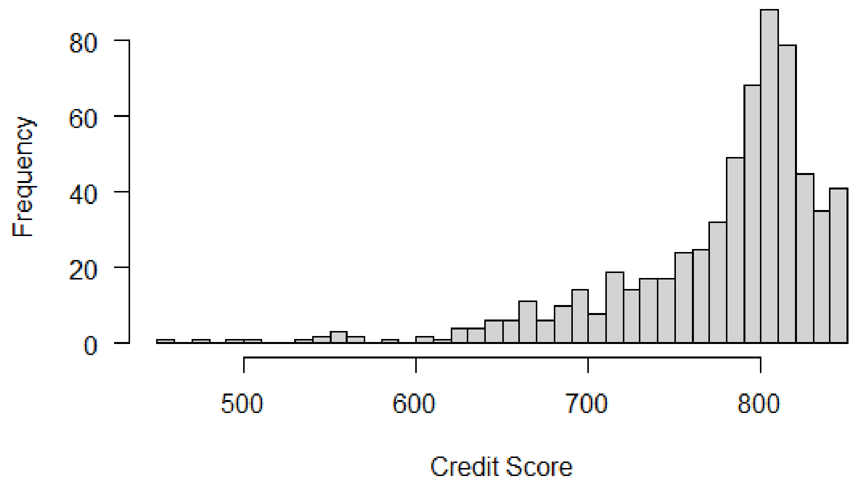
Notes: This figure presents a frequency histogram of the GoFundMe amounts raised by households, aggregating when there are multiple GoFundMe campaigns per household. This histogram excludes an extreme outlier in which one household raised nearly $300,000.

Figure 6: Histogram of income



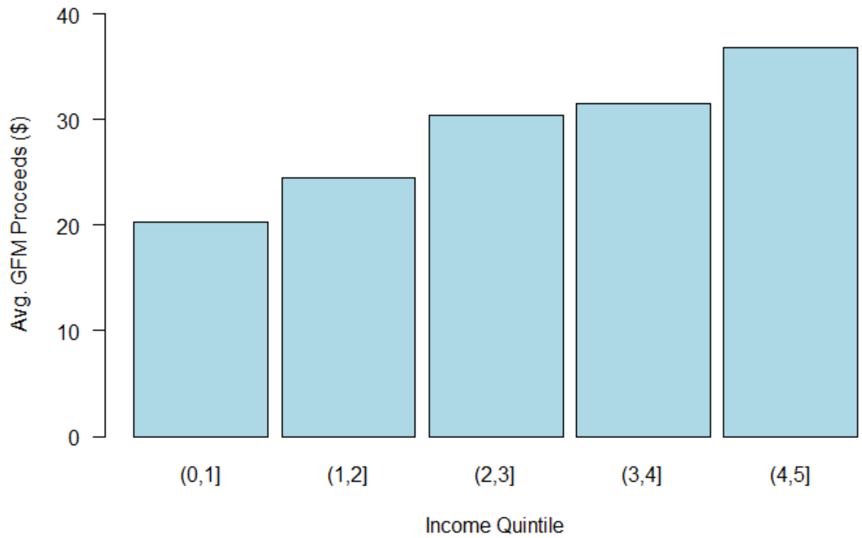
Notes: This figure presents a frequency histogram of income across households in our sample. The data uses Experian's income estimates aggregated across adults in same household.

Figure 7: Histogram of credit scores

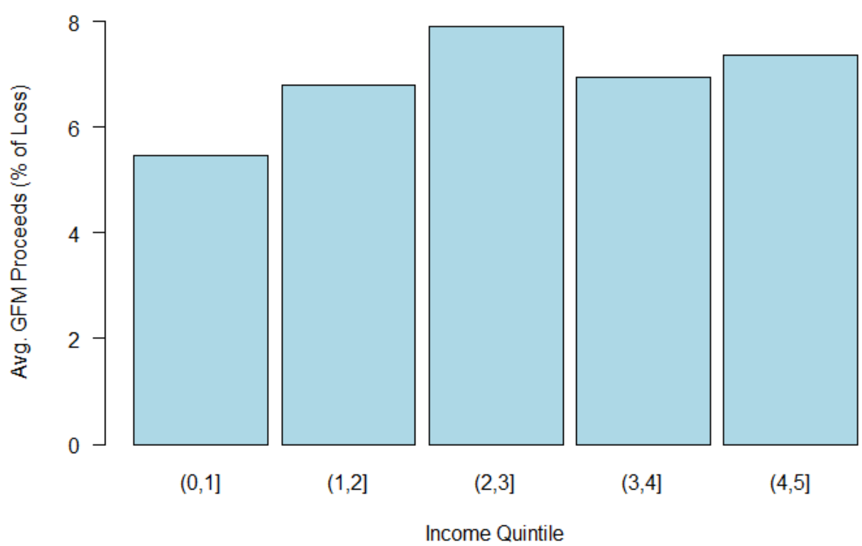


Notes: This figure presents a frequency histogram of Experian's Vantage Credit Scores for household beneficiaries of Marshall Fire GoFundMe campaigns. Credit score is averaged across adults in the same household.

Figure 8: GoFundMe proceeds versus income



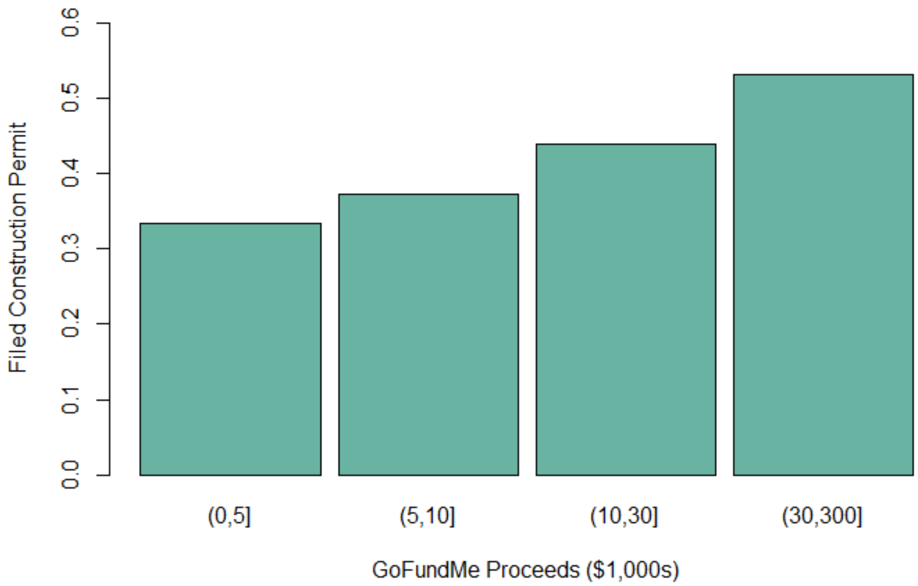
(a) GoFundMe proceeds, mean within income bin (full sample)



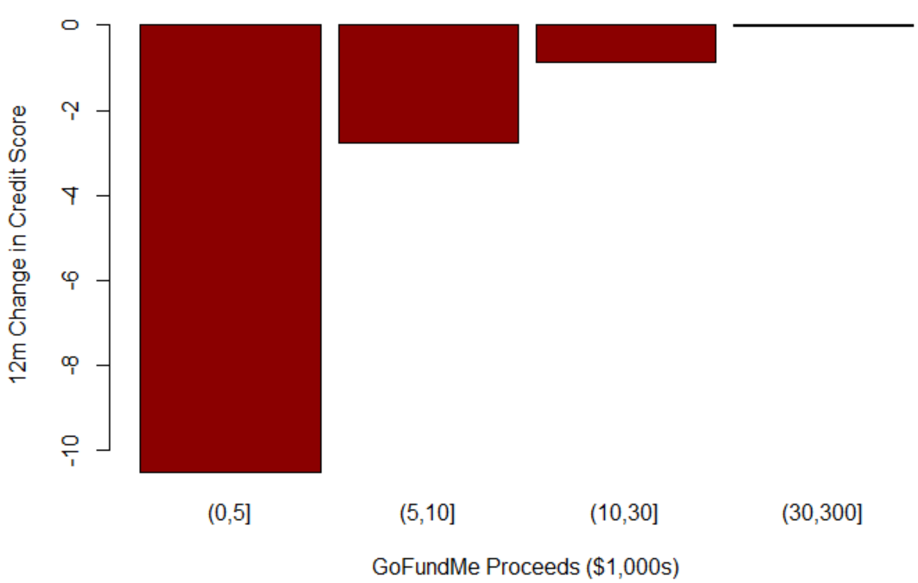
(b) GoFundMe proceeds scaled by property loss, mean within income bin (owners of total loss properties)

Notes: This figure plots average GoFundMe proceeds withing quintile bins of household income. Panel (a) includes all beneficiary households while Panel (b) restricts the sample to beneficiary households that own their home that was completely destroyed by the fire. In Panel (b), GoFundMe proceeds are scaled by the estimated market value of the structure lost to the fire.

Figure 9: Recovery versus GoFundMe proceeds



(a) Probability of filing for a construction permit over the 18 months post-fire



(b) Average change in credit score over the 12 months post-fire

Notes: Panel (a) of this figure plots, within bins of the GoFundMe proceeds raised by households, the fraction of households that filed for a construction permit. The permit must have been filed within the first 18 months after the fire to be included in this count. Panel (b) plots the average change in credit scores over the first 12 months after the fire within bins of the GoFundMe proceeds raised by households. Only those GFM beneficiary households that own their home and experienced a total loss (complete destruction of the structure of their home) are included this household-level sample.

Internet Appendix

Table A.1: Credit score distribution relative to other samples

This table presents the credit score distribution across subprime (Vantage score below 620), near prime (score between 620 and 720), and prime (820 and above) versus (Cookson et al., 2022), which uses the same classification on shale mineral recipients.

	Subprime	Near Prime	Prime	NA
GoFundMe Sample	2.4%	13.0%	78.9%	5.8%
Mineral owners	20.3%	29.5%	50.2%	
National representative sample	34.9%	24.6%	40.5%	

Table A.2: Determinants of GoFundMe proceeds, alternative property loss controls

This table presents OLS regressions using the specification in equation 1, where the dependent variable is logged GoFundMe proceeds ($). The data are aggregated to the household level and include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable is Log Income. All columns include a control for the square footage of the finished house area and fixed effects for whether the number of bedrooms and bathrooms in the property as well as whether the basement is finished. Log Mkt. Value of Structure is an estimate of the market value of real estate lost to the fire. Column 4 includes a vector of campaign-related controls. For households with multiple campaigns, campaign variables are averaged across campaigns. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

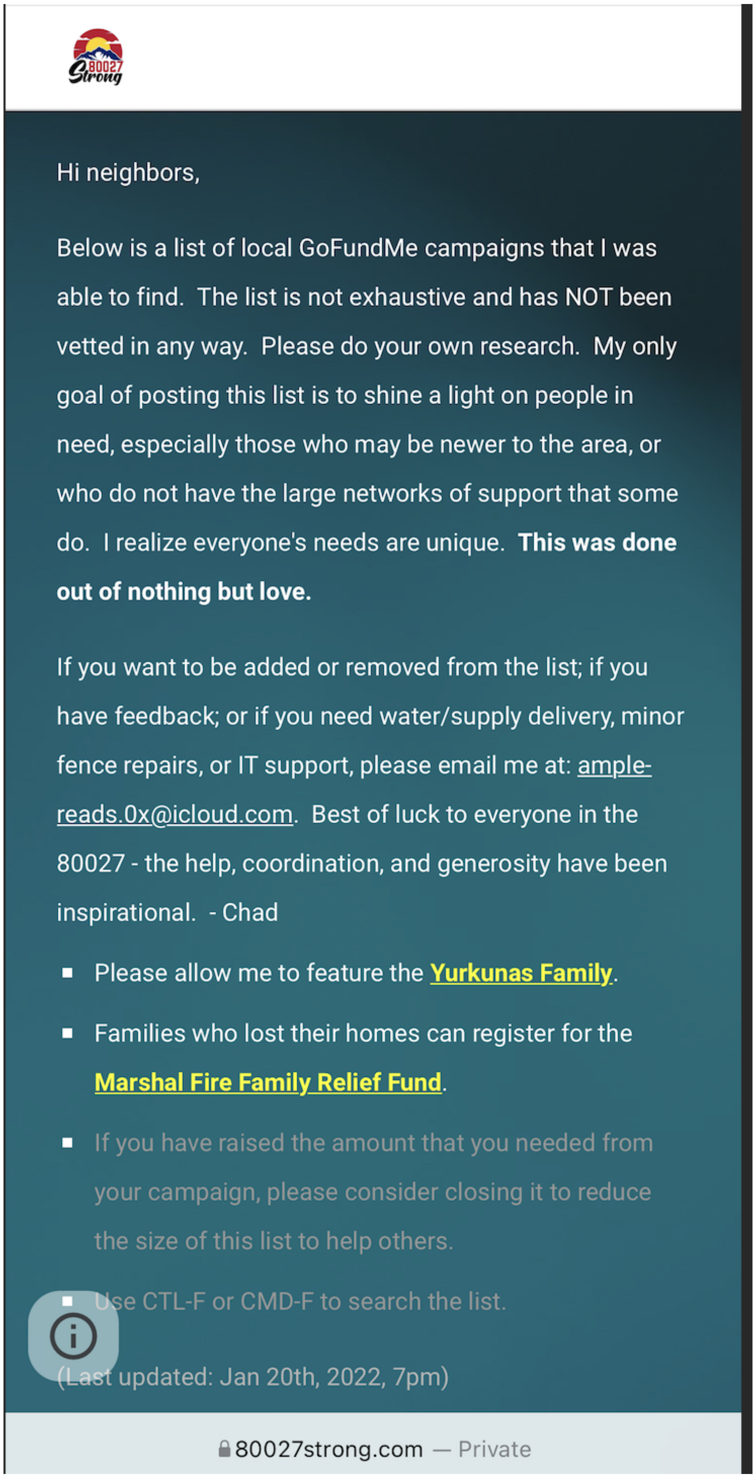
	Log GFM Proceeds			
	(1)	(2)	(3)	(4)
Log Income	0.444***	0.450***	0.474***	0.295**
	(0.139)	(0.138)	(0.138)	(0.145)
Finished Sqft	−0.0002*	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log Mkt. Value of Structure		−0.150	−0.109	−0.137
		(0.178)	(0.175)	(0.176)
# Adults in Household			0.078	0.039
			(0.067)	(0.067)
Mention Underinsurance				−0.187
				(0.167)
Mention Total Loss				0.747
				(0.557)
Mention Children				0.671***
				(0.125)
Mention Medical Condition				0.081
				(0.273)
Mention Pets				0.194
				(0.172)
Log # Words in Description				0.025
				(0.069)
# Errors per Word				0.106
				(0.078)
Has Picture				0.664**
				(0.319)
House-Type F.E.s	Y	Y	Y	Y
Observations	474	474	474	474
R^2	0.239	0.240	0.243	0.347

Table A.3: Effectiveness of fundraising by outside advocates

This table presents OLS regressions using the specification in equation 1, where the dependent variable is the log of a household or campaign's GoFundMe proceeds. All regressions include only those GoFundMe beneficiaries who own a home that was completely destroyed by the fire. The key explanatory variable, *Organizer is Not-family*, indicates that the GoFundMe campaign was organized by someone outside of the beneficiary's family (i.e., a friend or co-worker). In Columns 1-4, the data are aggregated to the household-level. In Columns 5-6, the data is at the campaign-level and include only household beneficiaries with multiple campaigns in order to include a household fixed effect. Designated specifications include a vector of campaign-related controls. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Log GFM Proceeds					
	(1)	(2)	(3)	(4)	(5)	(6)
Organizer is Not-Family	−0.074	−0.196	−0.061	−0.315	−0.435	−0.554
	(0.093)	(0.974)	(0.089)	(0.946)	(0.563)	(0.459)
Log Income	0.475***	0.458***	0.279***	0.244		
	(0.103)	(0.163)	(0.105)	(0.159)		
Log Mkt. Value of Structure	−0.201**	−0.201**	−0.212**	−0.211**		
	(0.102)	(0.102)	(0.092)	(0.092)		
# Adults in Household	0.047	0.046	0.026	0.025		
	(0.063)	(0.062)	(0.059)	(0.059)		
Organizer is Not-Family x Log Income		0.027		0.056		
		(0.213)		(0.207)		
Household- or Campaign-Level	H	H	H	H	C	C
Household F.E.s	N	N	N	N	Y	Y
Campaign Controls	N	N	Y	Y	N	Y
Observations	474	474	474	474	77	77
R^2	0.039	0.039	0.186	0.186	0.487	0.664

Figure A.1: Aggregation and Highlighting of GoFundMe Pages – 80027strong.com



Hi neighbors,

Below is a list of local GoFundMe campaigns that I was able to find. The list is not exhaustive and has NOT been vetted in any way. Please do your own research. My only goal of posting this list is to shine a light on people in need, especially those who may be newer to the area, or who do not have the large networks of support that some do. I realize everyone's needs are unique. **This was done out of nothing but love.**

If you want to be added or removed from the list; if you have feedback; or if you need water/supply delivery, minor fence repairs, or IT support, please email me at: ample-reads.0x@icloud.com. Best of luck to everyone in the 80027 - the help, coordination, and generosity have been inspirational. - Chad

- Please allow me to feature the **Yurkunas Family**.
- Families who lost their homes can register for the **Marshal Fire Family Relief Fund**.
- If you have raised the amount that you needed from your campaign, please consider closing it to reduce the size of this list to help others.
- Use CTL-F or CMD-F to search the list.

(Last updated: Jan 20th, 2022, 7pm)

80027strong.com — Private

Notes: This figure presents a screenshot from the webpage 80027strong.com, which maintained a list of Marshall Fire GoFundMe accounts with links to the pages, and basic summary statistics, including number of donors and amount raised. According to a May copy of the webpage, the list of GoFundMe accounts at 80027strong.com was updated through February 15th.