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# Network Replication of Inequality in Medical Crowdsourced Funding

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**Abstract**

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In 2018, over 250,000 American families found themselves unable to pay for medical care and turned to the online “crowdfunding” service GoFundMe to raise money online. The \$650 million dollars raised from these medical campaigns appear to have filled a sizable hole in the American social safety net. Yet crowdfunding is at heart a network process, and a large body of research shows that social networks can reproduce inequality. In this paper I show that medical crowdfunding replicates patterns of racial, ethnic, and geographic income stratification in ways that are consistent with network theory. Using 2,618 GoFundMe campaigns hand-coded for perceived race and ethnicity of the recipient, I show that Black and Hispanic beneficiaries receive substantially less money via their networks than White and Asian beneficiaries. Hierarchical linear models show that social network access via online sharing does not vary by race and ethnicity. However, network mobilization, measured in terms of the number and size of donations, varies substantially and produces unequal returns to campaigns. Variations in the number of donations can largely be explained by differences in estimated network financial capacity, but variations in donation size are not fully accounted for even in models including proxies for network income. Estimates of donor race and ethnicity indicate that donors of all races and ethnicities tend to give White recipients the largest donations and Black recipients the

smallest. Overall, I demonstrate that the use of “crowd insurance” in place of sufficient medical insurance reproduces existing patterns of inequality.

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## NETWORK REPLICATION OF INEQUALITY IN MEDICAL CROWDSOURCED FUNDING

It is well understood that social networks can play a role in the production and reproduction of economic inequality. For example, sociologists have long studied how differences in the structure, activation and returns to social networks affect access to employment (Granovetter 1973, [1974] 1995; McDonald 2011; McDonald et al. 2016; McDonald and Day 2010; Mouw 2002; Pedulla and Pager 2019; Silva 2018; Smith 2000, 2005). These studies examine the role of social networks in driving inequality on the income side of household ledgers, but another thread of research focuses on how smaller family-based networks are used to raise money in times of need. This use of “kin insurance” has been linked to racial inequality. Compared to Whites, Black and Hispanic families have lower access to capital via friends and family and more difficulty building wealth (Hall and Crowder 2011; McAdoo 1978; O’Brien 2012; Stack 1975).

Over the past decade, online “crowdfunding” services have promised an escape from the constraints of family networks for those facing financial hardship. The leading crowdfunding tool, GoFundMe, has millions of users and promises to “make it easy to inspire the world and turn compassion into action.” Access to a global pool of compassionate donors has particular appeal to the many Americans who have inadequate or non-existent medical insurance and need to improvise to overcome gaps in the social safety net. GoFundMe supports 250,000 medical fundraisers each year, raising over \$650 million dollars for medical expenses annually (GoFundMe 2019b). In practice the vast majority of crowdfunding campaigns do not “go viral,” and “inspire the world,” but instead are shared through smaller scale social networks, meaning that the campaign is likely to mobilize resources embedded in an existing network of family, friends, and friends of friends. Therefore, in spite of their promise, sites like GoFundMe may

replicate, or even amplify inequality. To quote Pedulla and Pager (2019) “On its surface the use of social networks appears race neutral, but patterns of social and economic segregation imply that their influence will consistently disadvantage members of historically marginalized groups.”

Other researchers have noted that the use of crowdfunding to close holes in the social safety net is likely to reinforce inequality. Snyder et al. (2017) argue that medical crowdfunding is a half-measure that weakens the case for systemic reform. Berliner and Kenworthy (2017) are concerned that network access and social media literacy create barriers for marginalized populations. In recent work using a sample of 637 hand-coded campaigns, Kenworthy et al. (2020) confirm that nonwhite users are indeed underrepresented on the site, and that nonwhite recipients receive fewer donations than Whites, with Black recipients receiving significantly smaller average donations. Yet despite the fact that crowdfunding is at base a network process, researchers have not explicitly examined how the structure of social networks and resources available through those networks might produce inequality in medical crowdfunding returns.

In this paper I extend the medical crowdfunding and network inequality literature by analyzing a geographically stratified sample of 2,618 GoFundMe campaigns that were hand-coded for perceived race and ethnicity of the beneficiary. I show that returns to crowdfunding vary dramatically by race and ethnicity. Inequality of returns is consistent with a model in which geographically and racially homophilous social networks translate economic inequalities among potential donors into disparities in online fundraising. However, even models that include controls accounting for campaign properties, network structure, and monetary capital do not fully account for racial disparities in returns. Subsequent analyses that include probabilistic estimates of donor race and ethnicity suggest that donors of all races and ethnicities tend to give White recipients the largest donations and Black recipients the smallest.

This paper applies insights from the study of network reproduction of inequality to the field of crowd-based fundraising, making several contributions. This is the first study to focus on how unequal access to monetary capital in networks of potential crowdfunding *donors* drives unequal returns for beneficiaries. I demonstrate that network mobilization in the form of online sharing, which does not require additional spending, does not vary based on the race and ethnicity of the beneficiary. However, Black and Hispanic recipients receive fewer and smaller donations than White and Asian beneficiaries. I show that networks of donors to crowdfunding campaigns are homophilous by race, and that variations in the estimated income of network members by geography, race and ethnicity can account for much of the deficit in returns. However, variations in expected network financial capacity by race, ethnicity and geography cannot account for all of the inequality in returns. In particular, anti-Black discrimination on the part of potential donors may be an additional driver of unequal returns. Overall, I demonstrate that racial and ethnic disparities in network financial capacity contribute to unequal returns in network crowdfunding campaigns. As a consequence, reliance on “crowd insurance” in the absence of sufficient medical insurance may serve to amplify existing patterns of inequality.

## BACKGROUND

The widespread use of GoFundMe medical campaigns in the United States is one piece of evidence that there are holes in the American social safety net. Even in the wake of the Affordable Care Act and a resulting reduction in the number of uninsured, medical care costs are a burden for millions of Americans. In 2017 28.5 million people in the United States did not have health insurance, and the population of uninsured is disproportionately poor and non-White (Berchick, Hood, and Barnett 2018). For people living below the poverty line in states that expanded Medicaid coverage under the Affordable Care Act, approximately 15% do not have

insurance, a number that rises to over 35% in non-expansion states (Berchick, Hood, and Barnett 2018). Almost 94% of White non-Hispanic Americans had medical insurance in 2017, while Asian Americans (92.7), Black Americans (89.4%), and Hispanic Americans (83.9) all had lower rates of insurance coverage (Collins et al. 2018). Even for those Americans who do have health insurance, high deductibles can strain family budgets. In 2018, 46% of under-65, privately insured individuals were covered by a high deductible health plan, up from 25% in 2010, and 13% of U.S. adults were enrolled in a private plan with a deductible of \$3000 or more (Collins, Gunja, and Doty 2017; Terlizzi, Cohen, and Martinez 2018). The high deductibles place a particular burden on nonwhite Americans. In a survey of adults 19-64 years old, 63% of Black respondents and 59% of Hispanics said that they would not be able to pay a \$1,000 medical bill within 30 days, compared to 40 percent of non-Hispanic whites (Collins et al. 2018). Against this background, those facing bills they cannot pay are increasingly turning to online crowdfunding platforms in search of financial support.

### Prior Medical Crowdfunding Research

Medical crowdfunding influences health care provision and funding via technological, market, and political mechanisms (Kenworthy 2019). Crowdfunding shapes health access via technology because crowdfunding platforms privilege those who have access to the technology and media skills to create effective online marketing campaigns. Technology also drives crowdfunding success because crowdfunding companies use proprietary and unaccountable algorithms to highlight particular campaigns (Kenworthy 2019). Crowdfunding shapes health care via the market because crowdfunding providers seek to profit from the inadequacy of social welfare safety nets. Crowdfunding campaigns may also affect the job market because they provide a public record of infirmity that might be used to discriminate against those seeking employment

and benefits (Kenworthy 2019). Finally, from a political standpoint, Kenworthy (2019), amplifying Snyder et al. (2016), fears that crowdfunding's premise of aid as something given by communities to those who are found deserving "shifts broader public values and discourses regarding health entitlements and citizen deservingness, consequently impacting efforts to ensure the right to health."

The lack of universal social programs in the United States has often been attributed to the desire to limit support to those viewed as "deserving" (Gilens 1999; Skocpol 1992, 2012), and much research into crowdfunding has explored how private giving is shaped by perceptions of which beneficiaries are deserving of help. Berliner and Kenworthy (2017:230) posited that crowdfunding requires beneficiaries to demonstrate "constellation of signifiers that position campaigns as deserving," and asked whether the ability to craft a compelling narrative and demonstrate "deservingness" is related to fundraising success. They coded 200 randomly selected GoFundMe campaigns which showed wide variability in number of respondents and amount of money raised. They found that nearly all campaigns make appeals to justify "deservingness" and that social media and medical literacies appear to be linked to the success in fundraising. Duynhoven et al. (2019) examined spatial patterns of Canadian medical crowdfunding use for cancer, finding that usage was higher in areas with middle to high socioeconomic status, perhaps because of higher computer access and social media literacy. Radu and McManus (2018) also focus on how beneficiaries present their campaigns, finding that victims of intimate partner violence attempt to demonstrate deservingness in their appeals for funding. Rhue and Robert (2018) explore the role of projected emotion in fundraising success, linking success to positive emotional valence of both the text and the photos posted by the requesters. People with some medical conditions may be perceived as more deserving of help

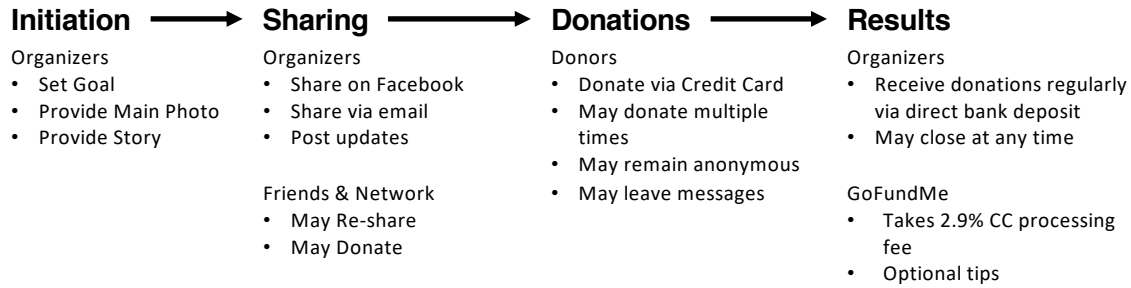
than others. Loeb et al. (2018) find that GoFundMe campaigns for breast cancer receive substantially more support than those for prostate cancer with prostate campaigns receiving a mean of \$1,400 on a mean request of \$16,000 compared to a return of \$16,000 on a mean \$30,000 request for breast cancer patients.

Kenworthy et al. (2020) explored the relationship between race and gender of GoFundMe medical campaign beneficiaries and campaign success. The authors found that nonwhite recipients were underrepresented in 637 campaigns randomly sampled from a corpus of over 165,000 medical crowdfunding campaigns. They also found that women were much more likely to be the organizers of campaigns and received fewer donations (but not lower donation amounts) than men. Black and other nonwhite recipients received fewer donations, and Black recipients received smaller average donations. The authors conclude that “much more research is needed to better understand how these disparities are created, and the social and technological mechanisms through which they are sustained and compounded.” This paper begins to address the mechanisms behind disparate results by turning the focus away from crowdfunding beneficiaries and onto the networks of potential donors whose actions are directly responsible for crowdfunding success.

### Crowdfunding as a Network Process

As a publicly recorded network process with beneficiaries from a variety of backgrounds, online crowdfunding provides a rare opportunity to study the way that networks may be involved in reproducing inequality. GoFundMe, with 250,000 new fundraising “campaigns” in the “Medical, Illness and Healing” category each year, is the most popular medical crowdfunding tool (GoFundMe 2019b). Each GoFundMe campaign follows the four-part process summarized in

Figure 1.



*Figure 1: Process of fundraising on GoFundMe.*

GoFundMe campaigns are initiated by an “organizer” to raise money for themselves or for a different beneficiary. Each campaign is represented online by a photo or video uploaded by the organizer, a short title summarizing the reason funds are needed, and a “story” describing the need for funds in detail. GoFundMe tells campaign organizers that “A great story will outline your cause clearly, in a way that is engaging to read. . . all while speaking from the heart.” (GoFundMe 2019a).

Q Search | How it works ▾ | Start a GoFundMe

gofundme Sign in | Share Donate

## Beat breast cancer with B [redacted]

**\$7,827** raised of \$10,000 goal

84 donors | 1.2K shares | 90 followers

[Donate now](#)

[Share](#)

[Penuel Corbin](#)  
\$87 • 4 mos

[Danielle Wynne](#)  
\$20 • 5 mos

[Jon LeClair](#)  
\$50 • 5 mos

[Candace Brey](#)  
\$100 • 5 mos

[Lisa Polinsky](#)  
\$25 • 6 mos

[See all](#)

[Destiny G \[redacted\]](#) is organizing this fundraiser on behalf of B [redacted]

Created July 31, 2018 | Medical, Illness & Healing

I am starting this gofundme campaign for my best friend B [redacted] and this is the story of why.  
The beginning of July 2018, B [redacted] found a lump on her right breast. She made an appointment to have it checked and was scheduled for a mamogram. Following the mamogram, she found in the doctor's notes that there was what's called a BI-RADS test performed. The test rates masses like these on a scale from 0-6 with 6 being positive for cancer... the lump was rated at a 5, giving it a 95% chance of being malignant.

A few days later came her biopsy and on July 13, 2018 she was diagnosed with breast  
[Read more](#)

Figure 2 Example of a GoFundMe campaign captured in 2019.

Engaging potential donors via social networks is central to GoFundMe's recommended methodology. GoFundMe urges organizers to link their campaigns to Facebook accounts and reminds users that "sharing is the key part to getting donations on GoFundMe. If you aren't sharing your campaign with your friends and family, then it's likely not going to get donations" (GoFundMe 2019b). Online social network sharing is only one avenue for dissemination of the campaigns. Campaigns are also shared via emails sent to social networks associated with workplaces, churches and volunteer organizations. Organizers attempt to mobilize initial recipients of requests to forward the request to their own social networks.

## Network Reproduction of Inequality

In and of themselves, networks are neutral structures, but when they are used to access information, opportunities, or money, the resources available to network members can amplify or ameliorate existing inequalities. In particular, social networks frequently connect individuals with similar characteristics, a phenomenon known as homophily. When networks are homophilous, access to resources may be limited to members of groups that already have them, as when access to professional jobs depends on membership in an “old boys” network composed primarily of White men (McDonald 2011). Network-driven inequality has been particularly well studied in the domain of employment search (McDonald 2011; McDonald et al. 2016; McDonald and Day 2010; Mouw 2002; Pedulla and Pager 2019; Silva 2018; Smith 2000, 2005), and my study of network inequality in crowdfunding builds on the concepts established in that field.

Inequality of returns to networks may arise from differences in the size and structure of the network, the resources available via network alters, or the motivation and ability of network alters to deliver those resources. Following Lin (1999), differences in returns due to network size and available resources are categorized as differences in network *access*, and differences in ability or willingness of network alters to generate positive returns are categorized as differences in *mobilization*. The relative importance of differences in network access and returns has informed much of the research into network inequality in job search. For example, Smith (2000) evaluated a variety of contributors to network mobilization in employment search including properties of the job seeker, the influence of the referrer, and the strength of the tie between the job seeker and the referrer. Smith found that weak ties were effective for high SES job seekers and that White men were able to take particular advantage of influential ties. In a further study of the cause of racial disparities in hiring, Smith (2005) found that “defensive individualism” in the

form of a desire to protect precarious job positions partially explained differences in network mobilization among low SES Black men.

McDonald, Lin and Ao (2009) find that unequal returns to network job search may depend on different mechanisms for different groups. They find that network access to job leads via casual conversations is lower for White women and Hispanics than for White men and Black respondents. For Hispanics, the lower number of leads is explained by smaller and more isolated networks compared to other groups. Black respondents, while receiving an equal *quantity* of leads through their networks, received fewer leads for supervisory jobs than White men, as did White women and Hispanics. The differences in returns highlight the importance of not only network structure and mobilization, but also the quality of resources obtained when a network is mobilized.

Pedulla and Pager (2019) conducted a longitudinal study of job seekers to examine the mechanisms that allow White job seekers to gain more from their networks than Black job seekers. Following Lin, they define “network access” as access to the information and resources that flow through social networks, and “network returns” as the benefits that arise from the use of networks. Pedulla and Pager (2019) find that *access* to network resources, in this case information about available jobs, does not explain differential success in job search. Instead, the placement of referrers within firms along with differences in mobilization of social capital are associated with poor returns for Black job seekers. The study does not find direct evidence of discrimination among employers, given equal mobilization and placement of referrers (Pedulla and Pager 2019).

Of course, substantial research shows that discrimination in hiring remains a barrier to employment (Pager 2003; Pager and Shepherd 2008; Quillian et al. 2017; Quillian, Lee, and

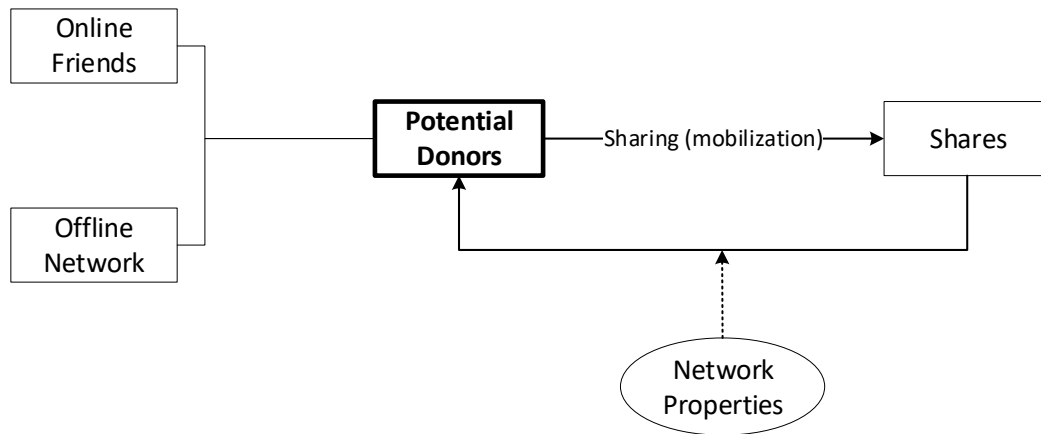
Oliver 2020). In one of the few studies to directly evaluate the role of discrimination in network-mediated job referrals, Silva (2018) examined the role of network intermediary race and employer prejudice on hiring. Silva (2018) showed that the race of the referrer, the race of the applicant and the level of employer prejudice measured by Implicit Association Tests all contribute to the rate of job offers (Silva 2018). Given the prior research on the uses of networks in job search, any study of disparate network outcomes by race should consider the roles of network access, network mobilization, and the possibility of discrimination on network efficacy.

### Applying Models of Network Inequality to GoFundMe

The concepts of network access and mobilization can be leveraged when building a model of network efficacy in GoFundMe. For each GoFundMe campaign, success depends on *access* to a network of potential donors, the *financial capacity* of the network, and *mobilization* of the network to share and donate to the campaign.<sup>1</sup> I define network access in terms of the (unmeasured) number of potential donors, that is, the number of people who become aware of the campaign by any mechanism. The term “financial capacity” refers to the income or wealth of potential donors. Returns from those donors are most meaningfully defined in terms of the money raised. Mobilization of the network, the link between access and returns, is reflected in sharing and donations. It is critical to note that network access and network mobilization are closely interrelated. The number of potential donors (network access) is dependent on the number of shares.

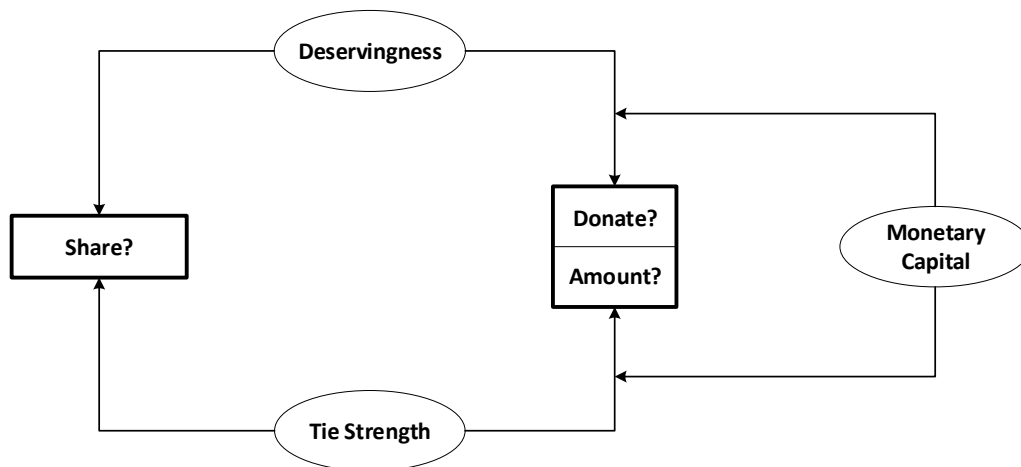
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<sup>1</sup> Job search studies are somewhat inconsistent in how they categorize resources available through a network. On one hand, network access is defined in terms of both the network structure *and the resources accessible through* the network (Lin 1999). On the other hand, Pedulla and Pager consider differences in placement of referrers not as a difference in available resources, but as a reason for variation in returns. I find it clarifying to explicitly break out the resources being accessed (in this case network financial capacity) from network structure and mobilization.



*Figure 3 Conceptual model of network access. Access depends on sharing (a type of mobilization) and network degree and density.*

A conceptual model for network access is shown in Figure 3. In this model, the number of potential donors (network access) is driven by the organizer’s online and offline connections, and the amount of sharing. The size of the campaign organizer’s first-degree network directly shapes the number of people who see a campaign. Organizers who have large online friend networks can guarantee a minimum number of online “impressions.” The number of new potential donors will increase with additional online social network sharing; more sharing is associated with greater access. The average number of new potential donors reached by each share depends on the density and average degree of the network.



*Figure 4: Conceptual model of network mobilization for a potential donor.*

Turning to network mobilization, the conceptual model shown in Figure 4 identifies two abstract factors that might cause a potential donor to share the campaign. First, the model holds that the stronger the social tie between the potential donor and the beneficiary, the more likely donors are to share the campaign. Second, a sense that the beneficiary is “deserving” of aid will mobilize potential donors to take action on the beneficiary’s behalf. Deservingness and tie strength also shape decisions to donate to the campaign, but the effect is moderated by a third factor: money available to donate to a campaign.

Tie strength, or the relationship between the donor and the beneficiary, can affect mobilization in a number of ways. In the case of close emotional attachment between the donor and beneficiary, the donor will be more likely to donate and share for simple affective reasons: we want to help the ones we love. Monetary payments and public sharing also convey meaning both to the beneficiary and to the broader community (Zelizer 1997). Social media sharing is always visible to the sharer’s network, and generally visible to the organizer and beneficiary of the campaign. On GoFundMe, recipients typically see the names of donors, and the majority of donors also choose to publicly list a name along with their donation. For direct ties, these

donations demonstrate the commitment of the donor to the beneficiary and may strengthen the relationship between donor and beneficiary. In situations with dense, overlapping, strong ties, public donations also demonstrate to the community that the donor is doing their part to support fellow community members. Given equal access to monetary capital we would expect people with closer ties to the participant to donate more frequently and in greater amounts.

Potential donors are more likely to take action on behalf of a campaign beneficiary if they view the campaign as “deserving.” Deserving campaigns evoke sympathy and a belief that support will help remedy an unfair or unfortunate situation that was not caused by a beneficiary’s actions. The concept of deservingness has played a significant role in the development of the American social safety net, which favors means testing and targeted benefits over universal programs (Skocpol 1992). On GoFundMe, all campaigns are accompanied by a story with at least one photograph – the convincingness of the story and the emotions it invokes are likely to affect donors’ impressions of the worthiness of the beneficiary. For example, campaigns on behalf of children may be viewed as deserving given the contemporary sense of the “priceless” nature of modern childhood, and the priority given to public social support for children and their mothers (Skocpol 1992; Zelizer 1994). Or, the nature of the disease or disability may be a marker of deservingness with donors may be more likely to support people who are suffering due to cancer than those who need a liver transplant because of alcoholism. Finally, the magnitude of the burden placed on the beneficiary and their family may be interpreted in terms of deservingness: if the need is large, potential donors may feel the beneficiary warrants more support.<sup>2</sup>

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<sup>2</sup> Note that the amount of money raised and amount of money requested may also be correlated if campaigns raise their requests *after* they have proved successful – so one should be careful about over-interpreting the causal relationship between these factors.

*Network Financial Capacity and Returns.* The aim of crowdfunding is to raise money for a beneficiary, so the financial resources of potential donors are a key determinant of the success of a campaign. While the conceptual model presented here posits that the decision to donate is affected by tie strength and deservingness, regardless of how close and deserving they find the beneficiary, donors without sufficient monetary capital simply cannot make large donations.

When a potential donor with low financial capital has a very close relationship to a person in need or is a member of a tight-knit community, we might expect them to provide a small donation as an expressive gesture. However, donors with low financial capital are likely to simply forgo donations to those with whom they have weak ties. On the other hand, for a wealthy donor, a meaningful donation to a strong tie might be quite large – nearly half of campaigns in my sample received at least one donation of \$1000 or more and 7% received at least one donation of \$5000 or more. Potential donors with significant financial resources also have the financial flexibility to make a donation to a campaign based solely on deservingness, regardless of social tie.

If networks tend to include many potential donors with similar financial resources, individual decisions of potential donors will combine to yield substantial differences in total returns to campaigns. For networks predominantly populated by people who own substantial monetary capital, one would expect some large donations from strong ties, and many donations from weak ties. For networks where members tend to have low financial resources, donations would tend to be for smaller amounts, and potential donors with weak ties to the beneficiary would be more likely to forgo donations entirely. As a result, beneficiaries embedded in high-financial-capacity social networks would tend to receive a greater number of donations and larger average donation sizes than beneficiaries embedded in low-financial-capacity networks.

In summary, while perceptions of deservingness may be correlated with returns to campaigns, campaigns perceived as equally “deserving” may receive very different number of donations or different average donation amount based on the financial capacity of their network.

*Geographic, racial and ethnic homophily and network financial capacity.* The conceptual model presented thus far argues that *if* potential donor networks are composed of people with similar financial resources, individual decisions about donations combine to yield disparate outcomes for beneficiaries. Though there is no way to directly establish the financial resources available to members of a potential donor network, correlations between established patterns of network homophily and patterns of economic inequality imply that financial resources will tend to be correlated within a given network of potential donors, especially among the vast majority of campaigns that fail to “go viral.” In particular, geographic, racial and ethnic homophily, combined with patterns of geographic and ascriptive income inequality, provide a basis for modeling network financial capacity and estimating its impact on returns.

*The impact of geography on expected returns.* Social networks tend to be shaped by geography. In general, the likelihood of friendship with an individual drops with distance (Backstrom, Sun, and Marlow 2010; Mok and Wellman 2007). In telephone networks, the likelihood of a connection between people has been shown to fall exponentially with distance (Lambiotte et al. 2008; Onnela et al. 2011). Even in the age of online social media, physical proximity is a strong determinant of “friendship” in online social networks (Backstrom, Sun, and Marlow 2010; McGee, Caverlee, and Cheng 2013; Rout et al. 2013). Facebook data aggregated at the county level shows high levels of geographic homophily, with much of the geographic variation in the concentration of friendship ties based on the prior residential mobility of county residents. For a typical county, more than half of all Facebook friends live within 50 miles of

county residents, even though only 0.7% of U.S. residents live within that radius (Bailey et al. 2018). The tendency of networks to be local allows me to exploit geographic variation in wealth and income to gain leverage on what financial resources might be available in the networks of potential donors associated with GoFundMe campaigns.

In addition to affecting outcomes via geographic income variation, geographic concentration of social network ties may affect the number of potential donors who see a campaign. Social networks in urban areas tend to be more segmented and have fewer overlapping ties than the networks of people who live in rural areas (Beggs, Haines, and Hurlbert 1996; Marsden 1987; White and Guest 2003). These differences are likely to affect the rate of information diffusion via bridging ties to other communities, and in high population areas should lead to a higher number of new potential donors exposed to the campaign for each social media share.

*Racial homophily and expected network monetary capital.* Decades of research has documented that racial homophily occurs in a wide range of networks. Within-race network connections occur at a much higher rate than chance in core discussion networks, workplace networks, school networks and online social networks (DiPrete et al. 2011; Marsden 1987; McPherson, Smith-Lovin, and Brashears 2006; McPherson, Smith-Lovin, and Cook 2001; Moody 2001; Smith, McPherson, and Smith-Lovin 2014). In contrast to expectations of the diversity of weak ties, extended acquaintanceship networks also tend to be segregated by race and ethnicity (DiPrete et al. 2011). Among minorities, Black Americans are most likely to have highly segregated acquaintanceship networks relative to expectations of random mixing.

Acquaintanceship networks of Hispanic and Asian Americans are also segregated, but to a lesser extent (DiPrete et al. 2011).<sup>3</sup>

Racial homophily leads to inequality in network monetary capital because it occurs in tandem with racial economic inequality. Black and non-White Hispanic U.S. residents have lower access to monetary capital, on average, than Whites and Asians. In 2018 Black families had the lowest median household income (\$40,258) of the Census Bureau's four major race and ethnic categories, and Hispanics had median household incomes of \$50,486. Asian (\$81,331) and White non-Hispanic (\$68,145) and households had substantially higher median incomes (U.S. Census Bureau 2018). These income differentials are quite large, but the history of institutional racism in the United States means that household wealth stratification is even larger (Oliver and Shapiro 2006). In 2016, median wealth held by non-Hispanic White families (\$171,000) was 10 times higher than that of Black families (\$17,600) and more than eight times higher than the \$20,700 median for Hispanic families (Detting et al. 2017)

Racial inequality and geographic concentration of social networks can compound one another in ways that have been most thoroughly studied for Black Americans. Middle class Black and Hispanic families tend to live in neighborhoods with higher levels of poverty than their white peers, and middle class Black neighborhoods are more likely to be surrounded by poor neighborhoods than middle class white neighborhoods (Pattillo 2005; Quillian 2012; Sharkey 2014). These factors might lead the networks of Blacks to have even lower access to financial capital than Whites with similar incomes.

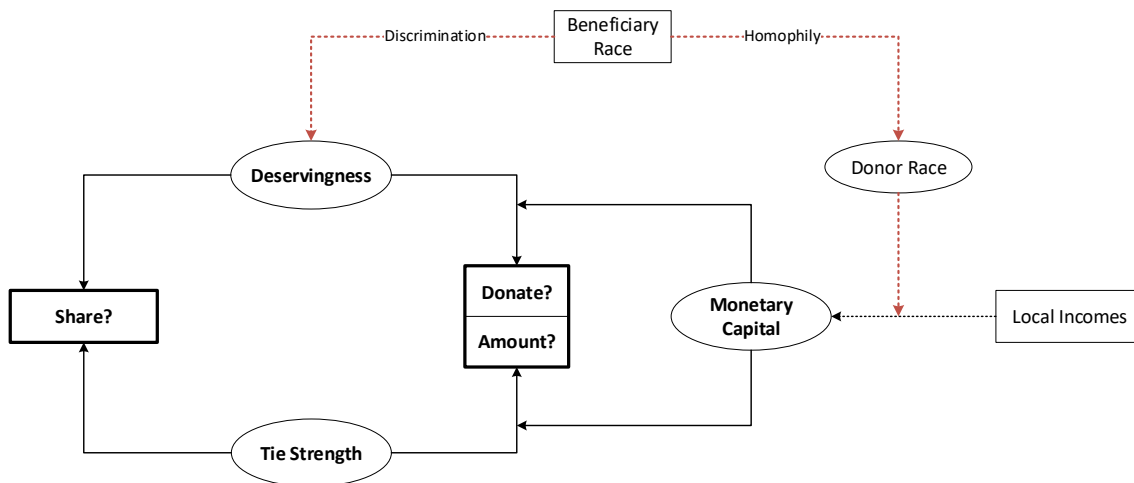
If patterns of homophily hold in the case of networks used for crowdfunding, Black and Hispanic beneficiaries will have a disproportionate share of same-race donors. Because of racial

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<sup>3</sup> DiPrete et al. note that due to the large proportion of White people in the United States it is difficult to measure "excess" homophily for Whites.

income and wealth inequality, those donors will be expected on average, to have lower access to monetary capital. Given these patterns of inequality in network financial capacity, Black and Hispanic crowdfunding beneficiaries would receive fewer and smaller donations on average than White and Asian beneficiaries, even in the absence of discrimination on the part of potential donors.

*Model of mobilization including race and geography.* Figure 5 presents a crowdfunding conceptual model that includes beneficiary race. Race may affect returns through one of two pathways: discrimination and homophily.



*Figure 5: Impact of beneficiary race on network mobilization. Monetary capital available to donors is correlated with donor race and local income distributions. Patterns of homophily mean donor race is more likely to match beneficiary race than would be expected under random mixing*

Deservingness, tie strength and monetary capital affect sharing and donations as described above. Mobilization in terms of sharing depends only on deservingness and tie-strength, but mobilization in terms of donations also depends on monetary capital available to the donor. Given that most network ties are local, monetary capital available to potential donors should be correlated with local income levels. The homophily pathway leads to unequal

outcomes because the race of network alters is more likely to match the race of the beneficiary than would be expected by chance, and monetary capital available to potential donors is correlated with the distribution of monetary capital by race. This strength of this effect is correlated with regional income stratification by race, which varies significantly. For example, the median income for Black households is 77% of White household income in Dover Delaware (\$44,000/57,000) and 26% in San Francisco (\$30,000/116,000).

In the discrimination pathway, potential donors view certain racial and ethnic groups as less deserving, and are less willing to mobilize on behalf of their campaigns. In the American context, substantial research indicates that Black and immigrant Hispanic residents are viewed by White Americans as less deserving of social support from government programs (Gilens 1996, 1999; Skocpol 2012). If the discrimination pathway is active, campaigns on behalf of Black and Hispanic beneficiaries will receive fewer donations, and smaller donations than those of White Americans, just as one would expect if the homophily pathway were active. The fact that the discrimination and homophily-based pathways produce similar outcomes is to be expected: institutional and interpersonal racism and discrimination created racial and ethnic inequality of monetary resources in the first place. However, if the discrimination pathway is active, one would expect differences in perceived deservingness to also be reflected in *sharing* by race and ethnicity. Evidence that campaigns are preferentially shared based on race and ethnicity of the recipient would be clear evidence of discrimination at work.

## HYPOTHESES

Assuming that the homophily pathway outlined above is at work, I offer the following hypotheses. After taking variation in “deservingness” and social network size into account

H1. Mobilization in terms of sharing does not differ by

- a. race and ethnicity or
- b. by local income levels.

In a model without discrimination, sharing depends only on deservingness and tie strength.

#### H2. Mobilization in terms of number of donations

- a. Is higher in locations with higher incomes.
- b. Is higher for high income racial and ethnic groups than low income groups.
- c. Varies depending on *local* income stratification for recipient's race and ethnicity.

#### H3. Average donation size is

- a. Is higher in locations with higher incomes.
- b. Is higher for high income racial and ethnic groups than low income groups.
- c. Varies depending on *local* income stratification for recipient's race and ethnicity.

## DATA AND METHODS

Many of the concepts central to the framework outlined above are not directly observed on the GoFundMe platform, so I begin this section with a short overview of how I operationalize those concepts. My analysis integrates three data sources. I analyze information from 2,618 medical crowdfunding campaigns, including 412,837 individual donations from the GoFundMe website. I used online raters to estimate the race, ethnicity, gender and age of campaign beneficiaries for these campaigns. I combine the GoFundMe and rater data with population and income data from the American Community Survey as well as name frequency tables from the U.S. Census Bureau.

The **size of the potential donor pool** cannot be directly determined. However, the GoFundMe data includes the number of online Facebook friends of the campaign organizer, along with a count of social media shares. While offline network size, and the density and average degree of the online network are not known, these properties are correlated with population size, and I include log local population size as an independent variable in models as detailed below.

I do not attempt to build a synthetic measure of **deservingness**, but my models include several covariates that may account for perceptions of deservingness. Models include a binary covariate for children (rated age under 18), and include a covariate for the campaign's monetary goal, an indicator of the burden faced by the family. Models also include a rating of text sophistication for the story.

Neither **the race and ethnicity of donors**, nor the **race and ethnicity of beneficiaries** can be estimated with complete confidence. I used human raters to estimate the race and ethnicity of beneficiaries and employ probabilistic estimates of donor race and ethnicity based on surnames as detailed below. **Financial capacity** of the potential donor pool is operationalized using overall and race-specific median household incomes for relevant geographic areas.

## Data Overview

GoFundMe does not provide any access to their entire set of campaigns or an API for accessing the database, so I initiated searches of their website between February 2 and February 23, 2019, using city names as search terms. Search terms included the names of the 100 largest cities in the United States plus the two largest cities in each state if they were not included in that set. My web scraping code looked at the first 200 campaigns returned per search term, plus new ones that were added during the scraping period. I downloaded data for all campaigns that had been active

in the prior year. This initial search yielded 18,817 distinct campaigns of which 6,186 were in GoFundMe's medical category. The downloaded data includes the location (city name based on zip-code), fundraising goal, the amount of money received to date, the start date of the campaign, and a list of donations. Though the information was not visible in web browsers, GoFundMe campaign pages available prior to September 2019 included the number of Facebook friends for organizers of campaigns who had linked their accounts to Facebook. I was also able to extract the postal code of the location where the campaign was initiated from data hidden in the web pages.

The set of 6,186 medical campaigns was filtered in a number of steps to arrive at the 2,618 campaigns used in this analysis. Because campaigns with goals  $\leq$  \$100 appear to use their goal as a placeholder and campaigns over \$10 million do not benefit a single individual, I removed campaigns with these very large and small goal amounts as well as campaigns in locations with two or fewer campaigns leaving 6,082. Of these I filtered to the set of 3,372 campaigns that had Facebook friend and share counts available and had been online for at least 5 weeks. The 5 week cutoff was chosen because preliminary analysis showed most campaigns received no more donations after that time. Raters estimated race and gender information from campaigns still online after 4 months as described below. I re-scraped the data 6 months after the original access to update money raised. Only the campaigns that remained available at that time were included in the final dataset.

Campaigns generally received a relatively small number of donations. Over 95% of campaigns received fewer than 500 donations and 80% of campaigns received fewer than 200 donations. My sample included one truly "crowdfunded" campaign, with 100,000 shares, more than 5 times the number of any other campaign. This campaign, on behalf of a person injured in

a political protest, received significant attention in nationwide news coverage. I removed this outlier from the analysis below.

*Race and gender identification of beneficiaries.* Zuberi (2008:8) warns that when sociologists study race there's often a risk that "We are not learning from the data, we are in fact presenting data that we have generated by our own biases." Despite the use of an independent variable labelled 'race and ethnicity' it is important to be clear about what is being measured in this paper. Race and ethnicity of campaign beneficiaries reported in this study is determined by U.S. based online raters who view the campaigns on GoFundMe. These ratings are based on perceptions of race and ethnicity by raters who do not have any direct knowledge of the people involved. Though the text of this document often refers to beneficiaries' race, that should be considered a shorthand for "race and ethnicity as perceived by raters." For each campaign I had two Amazon Mechanical Turk workers examine the campaign on the GoFundMe site and choose values for Race, Ethnicity, Gender, and Age range along with information about the apparent relationship between the organizer and beneficiary. Raters were told to review photographs and read the full text of the campaign to answer these questions and to use names as potential markers Hispanic ancestry. For the purposes of this study, race and ethnicity were coded as 'hispanic' if ethnicity was marked as 'Hispanic', with 'white', 'black', 'asian' and 'other' comprising campaigns where the beneficiary is marked as "Not Hispanic." Agreement among raters was 93% on gender and 80% on race/ethnicity (87% on white/nonwhite). If the two raters did not match on the primary variables on race/ethnicity and gender I personally adjudicated the discrepancy by examining the campaign. Models estimated using only data where the online raters agreed showed very similar results, as discussed in the section on robustness checks.

*Table 1*

<b>Race/Ethnicity</b>	<b>n</b>	<b>Sample %</b>	<b>U.S. %</b>	<b>Female</b>	<b>Child</b>
White	1929	73.7%	61.5%	53.3%	20.6%
Black	247	9.4%	12.3%	49.4%	20.6%
Hispanic	321	12.3%	17.6%	50.5%	23.4%
Asian	81	3.1%	5.3%	55.6%	16.0%
Other	40	1.5%	3.4%	57.5%	27.5%

The relative frequency by race and ethnicity is shown in . In this sample, White beneficiaries are overrepresented compared to the population as a whole, and Black, Hispanic and Asian beneficiaries are underrepresented. Kenworthy et al. (2020) also found that Black beneficiaries were underrepresented in their randomly selected sample.

*Summary of campaign data.* Figure 6 shows medians and interquartile ranges for a number of statistics for the campaigns used in this analysis. A full table of summary statistics can be found in Appendix 1. Anova tests indicate that friend counts, amount raised, and mean donation show differences that are unlikely due to chance at a  $p < .001$  level, and goals are different at a  $p < .05$  level. Notably, pairwise t-tests show that organizers for recipients coded as Black have a higher number of Facebook friends than other groups at  $p < .001$ .

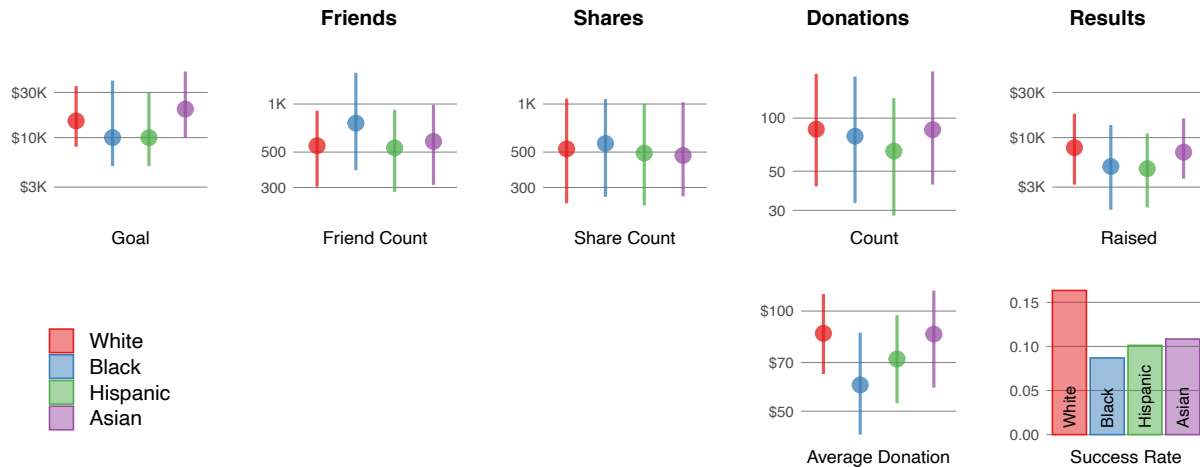
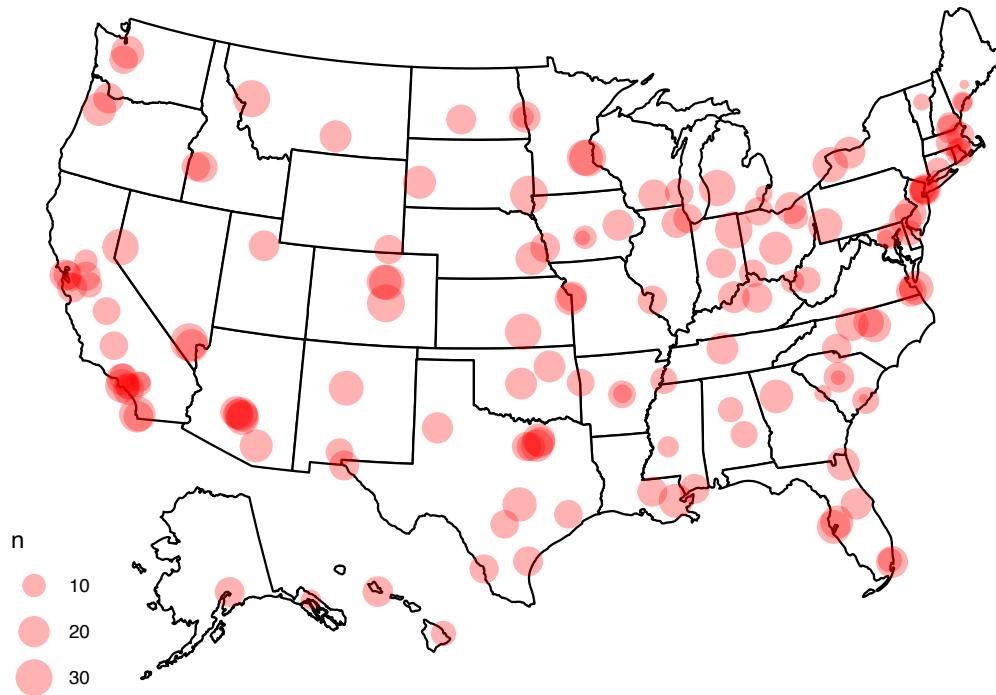


Figure 6: Median and IQR for GoFundMe Campaigns. Each campaign goes through a multi-step process of setting a goal, engaging prospective donors and receiving donations. Charts on top row use log scales.

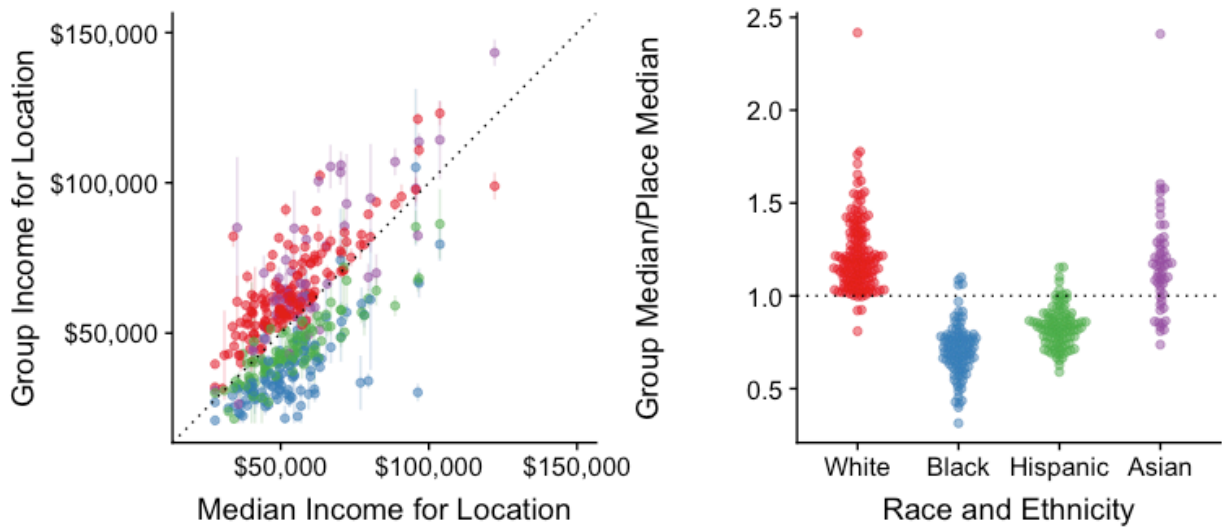
*Measures of network economic capital.* A critical element of the framework used here is the financial capacity of the network of potential donors. However, neither the pool of potential donors nor information about their economic circumstances is available in the GoFundMe data. To overcome this limitation, I exploit the fact that networks tend to be geographically concentrated and use place-specific median household income to proxy for available economic capital in the area. To capture the effect of racial homophily on financial capacity of the potential donor network I also include the place-specific *ratio* of median household income for the beneficiary's race and ethnicity to the overall geographic median. As shown in Figure 7, there is substantial geographic variation in both median household income and relative income by race in this dataset, enabling statistical models to estimate their effects independently. Median household incomes in the locations listed on GoFundMe campaigns in this dataset vary substantially from \$27,838 in Detroit to \$122,191 in Fremont, CA. The relative incomes of racial and ethnic groups also vary from city to city. In San Francisco, the median household income is \$96,000 overall, but only \$30,000 for people who report their race as Black on the ACS. In

Birmingham Alabama the estimated median income is roughly \$34,000: \$51,000 for those who report being White and \$29,000 for those who report being Black.

An important question is what is the “geographic area” to be considered when evaluating the effect of geographic concentration on available economic capital. I estimated models using estimates of median household income from the Census Bureau American Community Survey, 2013-2017 5 year estimates (U.S. Census Bureau 2018) for both the census “place” corresponding to the city listed on the GoFundMe campaign and the census-defined Core Based Statistical Area (CBSA) containing the organizer zip code. A census place is a contiguous area with legal boundaries, generally a city, or an unincorporated area with locally recognized name. When I refer to statistics for a “location” of a campaign, I am referring to defined census places. Places in this study range in size from Montpelier VT, population 7584, to New York City, with a population of over 8 million. A potential issue with the use of Census places is that legal boundaries can seem arbitrary. For example, New York City is a single census place but Fargo, ND and West Fargo, ND are considered different census places. Core Based Metropolitan Statistical Areas are defined based on commuting ties, rather than political boundaries, but they may not be ideal for estimating network capital because CBSA’s often span many areas with different income distributions. For example, New York City’s CBSA spans 23 counties in three states. In practice, models including household incomes based on census places yielded slightly better model fits than those using CBSA-level estimates, so I report them here. A comparison of models based on geography is included as an appendix.



*Figure 7 Locations listed for GoFundMe campaigns matched 149 distinct census places.*



*Figure 8: Income by racial/ethnic group in the dataset vs median income for the city. Variation in relative income ratios can be used to understand relationship between returns, race and financial capital.*

In addition to CBSA and “place” level estimates of racial/ethnic income, I also built models using income ratios based on the zip-code where the campaign originated. Zip-code level ratios may best represent network monetary capital if the network is made up of people with similar financial resources to the organizer. Place-based ratios may be preferred for representing monetary capital in a racially-homophilous donor pool for the whole city. Zip-code specific incomes are based on census zip code tabulation areas (ZCTAs). Two cautions are in order when using ZCTA estimates. First, because of smaller numbers of survey participants, zip-code level income estimates necessarily have higher margins of error, especially for minority group incomes. Second, actual zip-codes reflect routes used for postal delivery and don’t necessarily correspond to contiguous areas defined by the boundaries of census blocks. Census ZCTAs attempt to find a set of Census blocks that best match each zip-code. Thus ZCTAs are not ideal definitions of a geographic area, but are likely the best estimate of the income of the organizer. As demonstrated in the appendix 2, Zip-code level estimates of group income ratios resulted in

the best model fits and are reported below. The campaigns came from 111 CBSAs, covering 149 census places and 1288 distinct zip codes.

In this sample, most campaigns were initiated in zip codes that had *higher* median incomes than the city as a whole, regardless of the race of the beneficiary. Overall 62.4% of campaigns came from zip codes with higher median household incomes than the citywide median. This pattern may reflect financial barriers to initiating campaigns and supports the claim of Berliner and Kenworthy (2017) that the use of crowdsourcing itself requires cultural capital that may not be equally shared.

*Donation data.* I retrieved 412,837 individual donations for the campaigns included in this study. For each donation I retrieved the name associated with the donation, the amount of the donation and an estimated date based on text like ‘6 months ago’ or ‘2 weeks ago’. Because the estimated dates are not very precise, my models use the order of the donation as an independent variable, with 1 being the first donation, 2 the second and so on.

Donation amounts show a strong tendency to cluster near ‘round’ numbers, with common donation sizes increasing roughly geometrically rather than linearly. Donations for amounts of \$25, \$50, \$100, \$200, \$250, \$500 and \$1000 account for 73% of all funds raised. While the vast majority (88.4%) of donations are for amounts of \$100 or less, larger donations account for half of the dollars donated (51.7%). Large donations of \$1000 or more account for 19.6% of the funds raised, but only 1.2% of the donations. By contrast, donations of \$20 or less account for 3.6% of the funds raised and 22.0% of the donations. As shown in Figure 9, campaigns on behalf of White non-Hispanic and Asian recipients received more high-dollar donations on average than campaigns on behalf of Hispanic and Black recipients.

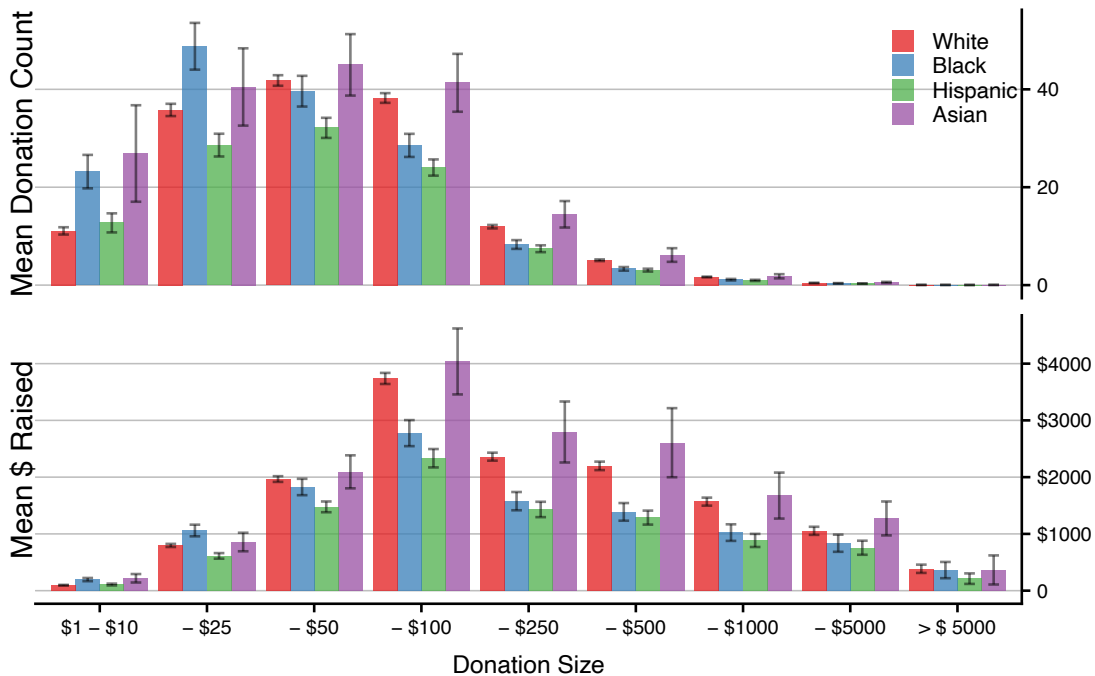


Figure 9: Mean number of donations per campaign by dollar range on top, mean value of those donations on the bottom. Much of the difference in returns is driven by the number of relatively large donations.

*Estimating race and ethnicity of donors.* In order to establish that patterns of network racial homophily apply to GoFundMe campaigns, it is critical to understand the race and ethnicity of donors. I use the surnames of donors to evaluate the likelihood that donor race and ethnicity matches beneficiary race and ethnicity. Each GoFundMe donation is listed with a donor name. Donors may choose to attribute their donations to “Anonymous,” and there is no guarantee that stated donor names match the name of the actual donor. However, donors — especially those known to the recipient — have an incentive to provide accurate names in order to demonstrate support for the recipient. Seventeen percent of donations are marked anonymous, while the remaining 83% are listed with a name. When names are provided, they are sometimes listed as the donor’s full name, (e.g. "Jane Smith), as multiple first names with with a surname ("Jane and John Smith") or as a family ("The Smith Family"). About 5% of donations include a first name and no last name.

I use location and donor surnames along with the `wru` R package (Khanna and Imai 2019) to estimate the probability that a donor belongs to each race and ethnicity category. The algorithm combines the Census Bureau list of racial proportions for 167,613 surnames combined with racial proportions of geographic areas to arrive at a Bayesian estimate of the likelihoods of a surname in that area corresponding to each of 5 racial and ethnic categories: non-Hispanic White, Black, Hispanic, Asian and Other. The surnames in the database cover 95.5% of the population, with the remaining 4.5% or 13 million people accounting for approximately 6 million rare surnames. Eighty-seven percent of the surnames I recovered for donors had an exact match in the name list. I calculated surname likelihood both using census place-level racial demographics, noting that most social network ties are between people in the same geographic area, and using unweighted national racial demographics.

The estimation of donor race yields probabilities that each donor name corresponds to each of the five racial and ethnic categories the census reports for surnames. Thus, each estimate represents uncertainty about the race and ethnicity of a donor. When I include donor race estimates in models, I retain the full set of five probabilities as covariates. To prevent evaluations of *beneficiary* race from becoming self-fulfilling predictors of homophily, I *do not* take the race of the beneficiary into account when calculating the probability that a donor surname is associated with a race.

## Statistical Models

The analysis of outcomes uses mixed effect hierarchical models with a random intercept for the census place (city) of individual initiating the campaign (Gelman 2007). Models to estimate overall campaign results use log dollars raised as a dependent variable. I use log share count as a dependent variable in estimating mobilization in terms of sharing and as an independent variable

when estimating mobilization in terms of donation count. In all cases, the dependent variable is represented in log form, as the data best fits a log-normal distribution (See Figure 10).

The base model specification is

$$\eta_i = \alpha_{j[i]} + \beta_i X_i$$

$$\alpha_j \sim N(\mu_\alpha, \sigma_\alpha^2)$$

Where

- $\eta_i$  is the estimated response for campaign  $i$
- $\alpha_{j[i]}$  is the intercept for the location  $j$  associated with campaign  $i$
- $\eta_i X_i$  is the set predictors for campaign  $i$
- $\mu_\alpha$  is the overall mean of locations means
- $\sigma_\alpha^2$  is the between-group variance for locations

The response,  $\eta_i$ , represents

$$\eta_i = E(\log(y_i^a))$$

where  $y_i^a$  is the dependent variable (share count, donation count or mean donation) for campaign  $i$  in location  $a$ . Count models for shares and donations using Negative Binomial estimation yield similar results.

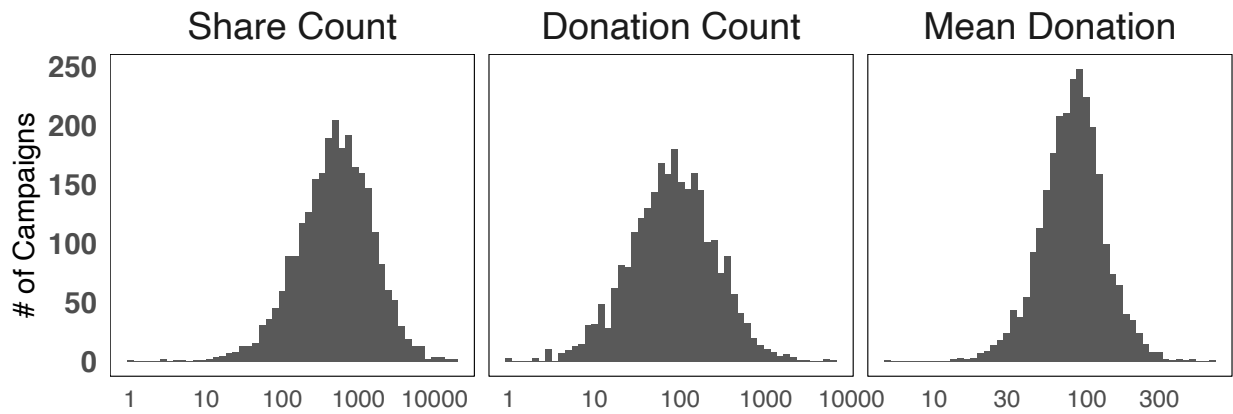


Figure 10: Distributions of dependent variables for campaigns. Log scales.

Place level independent variables include log population as a covariate correlated with the size of the potential donor pool. Independent variables estimated by raters include the race

and ethnicity of the beneficiary, as well as whether the beneficiary is a child (rated as being under 18 years of age). Deservingness as presented in terms of text-sophistication is reported using a Flesch-Kincaid grade level for the main story presented with the campaign.

When predicting individual donation amounts, models are nested hierarchical models, with varying intercept by campaign nested within varying intercept by location. Because common donation amounts increase geometrically rather than linearly (the three most common donation amounts are \$25, \$50, and \$100), models estimating donation counts use log donation amount as the independent variable.

I fit hierarchal models with the `lme4` package in R.

## RESULTS PART I – ESTABLISHING DISPARATE OUTCOMES

The basic statistical models for estimating overall network effectiveness are in Figure 11. Models 1 and 2 confirm conceptual model shown in Figure 3. Local population and income levels are clearly important determinants of success in fundraising. Increasing the number of Facebook friends by 1% corresponds to a roughly .06% rise in returns but increasing population in the census defined place by 1% translates to a .37% rise in amount raised. In addition, higher local incomes are associated with higher returns. For example, for a typical campaign with a \$15,000 goal in El Paso, TX, median local income of \$44,400, would be expected to raise \$5,380. If the median household income is doubled to \$88,800, approximately the median for Plano, TX, the estimated return rises to \$6,763.

Measures of “deservingness” also show large and significant relationships to returns. Raising the stated goal by 1% is associated with a .6% increase in returns, and campaigns on

behalf of children yield approximately 15% ( $e^{-14}$ ) more money than others.<sup>5</sup> In this set of models, changes to the sophistication of text do not seem to increase returns.

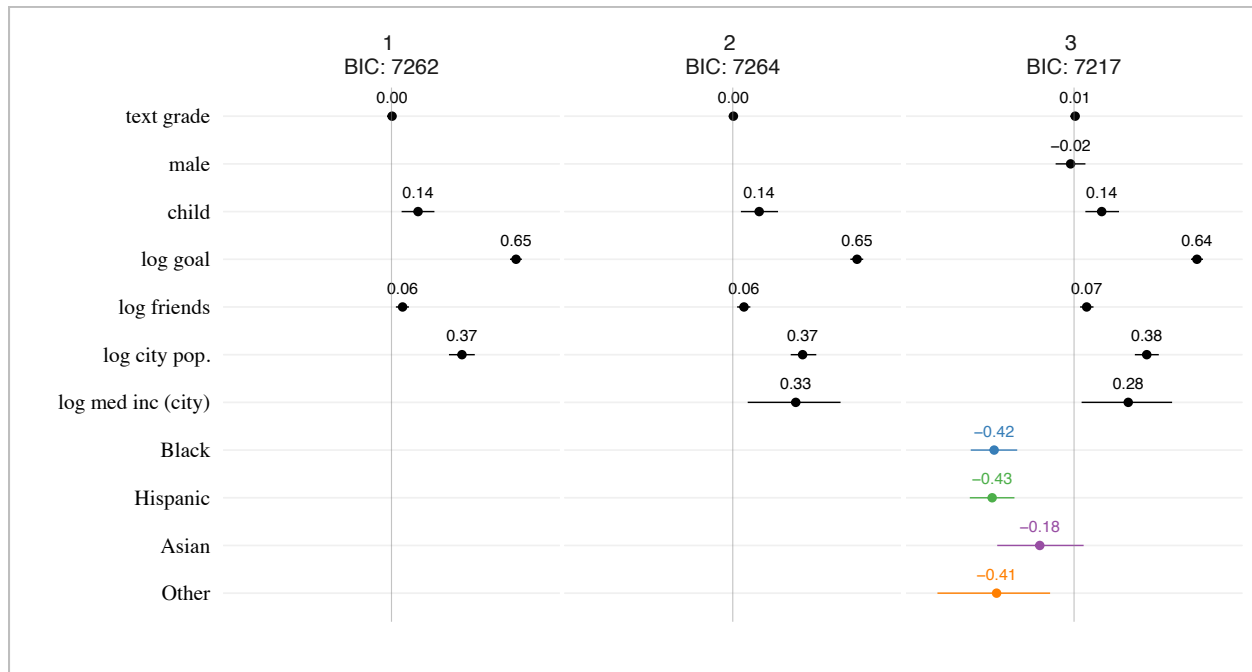


Figure 11: Models of log amount raised including bootstrap 95% confidence intervals.

A final prediction of the conceptual model presented in Figure 3 is that donations are likely to fall the greater the social distance from the giver to the receiver. In a separate model shown in Figure 16, I used donation order as a rough proxy for closeness of tie under the assumption that close ties are likely to learn about the campaign first and have a high likelihood of donating. The model yields a coefficient for log order of  $-.02$ . Though the parameter is statistically different from zero with  $p < .001$ , donation order accounts for very little of the observed variation in donations: if the model estimated a first donation of \$100, it would estimate that donation number 100 would fall to roughly \$87.

<sup>5</sup> Recall that successful campaigns may raise their goals, so the association of higher goals with higher returns may not be causal.

Model 3 in Figure 11, which includes covariates for deservingness, population and local income levels along with covariates for the race of the beneficiary, shows that Black, Hispanic and other non-White, non-Asian recipients receive less than 60% of the returns of White beneficiaries. After accounting for local population and “deservingness” measures, gender does not seem to be associated with outcomes.<sup>6</sup>

Translating the results into specific predictions, a campaign with a \$15,000 goal in Seattle Washington is predicted to yield \$6,322 for a Hispanic man, \$6,389 for a Black man and \$9,708 for a White man. The Bayesian Information Criterion (BIC), a penalized goodness of fit measure, provides a means of comparing models, with lower numbers being better. Guidelines developed with the BIC would indicate that the improvement is “very strong” evidence that race and ethnicity improve the model (Raftery 1995). These models confirm the results of earlier studies showing that Black beneficiaries receive lower returns from medical crowdfunding than White beneficiaries, and extend the result to Hispanic beneficiaries.

## RESULTS PART II: CAUSES OF DISPARATE OUTCOMES

Disparate outcomes by race observed in the prior set of results can be explained in terms of differences in network access (number of friends and shares) or by differences in mobilization (number of shares and donations and size donation amounts) or by discrimination. If differences in returns are driven by differences in network monetary capital, as my hypotheses predict, donations will vary by along with income variations by geography, race and ethnicity, but shares will not be affected by income levels.

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<sup>6</sup> I also estimated models including interaction terms for race and gender of beneficiary. These interaction terms did not show large or significant coefficients for race and gender in combination.

## Donor Homophily and Monetary Inequality

While racial and ethnic homophily in American social networks is a well-established pattern, this pattern has not been confirmed for networks consisting of donors to crowdfunding campaigns.

Using the race and ethnicity of a beneficiary to estimate financial capacity available in a network only makes sense if donor networks tend to be homophilous, so here I establish that these networks do indeed exhibit homophily.

While race of the beneficiary is directly coded from photos and other information in the campaign, we know little about the identity of donors, other than their names. Luckily for our purposes, the prevalence of specific surnames varies by race and ethnicity, and I exploit this fact to estimate the probable racial and ethnic background of donors. I then use these probabilities to estimate the degree of ethnic homophily for donors to medical crowdfunding campaigns. For each surname, the Census provides the number of U.S. people with the surname and probabilities of the surname occurring for 5 race/ethnic categories: White, Black, Hispanic, Asian, Other.

Most Asians and Hispanics in the U.S. have names that are distinctive to their own race and ethnicity. Ninety-six percent of the 437,000 people with the surname Nguyen report being Asian and 92% of the 1.1 million people named Garcia are listed on the census as Hispanic. White Americans' names also tend to be highly distinctive. For example, Ninety-five percent of the people in the U.S. with the surname "Olson" are White. Because many Black Americans are the descendants of enslaved people who adopted Anglo surnames after emancipation, Black surnames are not as distinctive. For a randomly chosen Black person in the U.S., the expectation would be that only 32.1% of the people who share their surname are Black.

My analysis computes the expected probability that *donors* to a set of campaigns come from each race/ethnicity. The computation is best demonstrated by example as shown for the

hypothetical 4 donors in Table 2. Each surname is associated with a probability of appearing in the census for each of the five broad categories of race and ethnicity. For this example, there was one donor with the surname “Chen”, two with the surname “Lee” and one with the surname “Smith.” The average probability a donor surname belongs to an Asian in this case is .453. Given that the U.S. population is about 5% Asian, this hypothetical set of donors is likely pulled from a pool of donors where Asians are overrepresented. Of course, with only 4 donors, one could not confidently estimate the makeup of the donor pool.

*Table 2 Hypothetical donor homophily data*

	Surname	P(White name)	P(Black name)	P(Hispanic name)	P(Asian name)	P(Other name)
1	CHEN	0.014	0.003	0.0052	0.961	0.0166
2	LEE	0.359	0.163	0.0189	0.422	0.0361
3	LEE	0.359	0.163	0.0189	0.422	0.0361
4	SMITH	0.709	0.231	0.024	0.005	0.0308
	<b>Average</b>	<b>0.360</b>	<b>0.140</b>	<b>0.0168</b>	<b>0.453</b>	<b>0.0299</b>

Turning to the set of 337,184 donations with listed surnames that match census names, I computed averages as in Table 2 separately for donors to each beneficiary race/ethnicity. I find that when the beneficiary is Black or Hispanic, the average probability that a donor is Black or Hispanic is more than twice what would be expected under random mixing for all U.S. residents. The probability that a donor name is Asian for an Asian recipient is over six times what would be expected under random mixing.

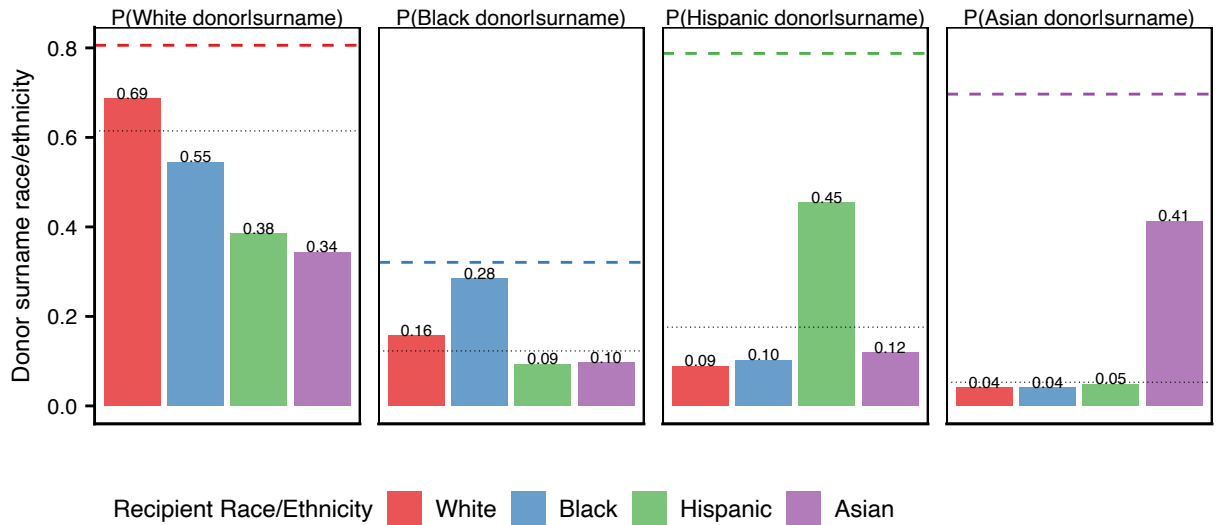


Figure 12: Donor surname match by recipient. Dashed lines represent expected values for “full homophily,” when all donors are from same donor race/ethnic group. Dotted lines are overall population belonging to group.

Figure 12 shows the observed mean probability that the donor’s name matches the recipient’s race. Dashed lines in the figure indicate the surname match expected if all donors were of the race and ethnicity for the panel. For Black donors and recipients, the observed surname match of .28 is close to the value of .32 expected if all donors were Black Americans. In all cases, donations are substantially more likely to come from same-race donors than would be predicted by chance, and in all cases donor networks are not completely homophilous by race.

The observed match percentages in Figure 14 reflect Bayesian estimation of donor race and ethnicity based on the assumption that the donor lives in the same city as the organizer. This assumption increases the estimated observed match for Blacks and reduces the observed match for Whites given the relatively higher proportion of African Americans in the sample locations. If donors were evenly distributed nationally regardless of the organizer location (an extreme assumption that contradicts findings linking returns to local incomes), the observed surname

match for Blacks falls to 0.18 and for Whites rises to 0.75. Surname matches stay similar for Hispanic and Asian donors under this alternate assumption.

I used Maximum Likelihood Estimation to estimate the underlying distributions of donors by race of recipient, using semi-constrained optimization. The likelihood function calculates a predicted “surname match” percentage for each race and ethnicity based on a simulated donor pool weighted by racial and ethnic group. The proportion of donors in the simulated donor pool matching the recipient race and ethnicity is allowed to vary without penalty. The proportions for other races and ethnicities are penalized as they vary from proportions expected for the rest of the population. The analysis estimates that over 70% of donors to Black beneficiaries are Black themselves, and about half of donations to Asian (54%) and Hispanic (51%) beneficiaries come from donors of the same race/ethnicity. Seventy-seven percent of donors to White beneficiaries are estimated to be White.

### Network Access

Success in crowdsourced fundraising depends on accessing a sizable potential donor pool, which in turn depends largely on the size of the organizer’s first-degree social network, network density and degree, and how many times the campaign is shared. In this section I evaluate evidence that these factors drive differences in returns by race and ethnicity.

The size of the organizer’s first-degree network, as measured by number of Facebook friends, cannot explain racial inequality in fundraising. Pairwise t-tests show organizers of campaigns for Black beneficiaries tend to have significantly *larger* Facebook friend counts than White beneficiaries, while other races and ethnicities are not statistically different from Whites. Similarly, in this sample, compared to White recipients, Hispanic and Asian beneficiaries tend to live in larger population centers and, other factors being equal, would be more likely to have

larger, less dense offline networks. These basic measures of network access would not explain the patterns of inequality of returns by race established above..

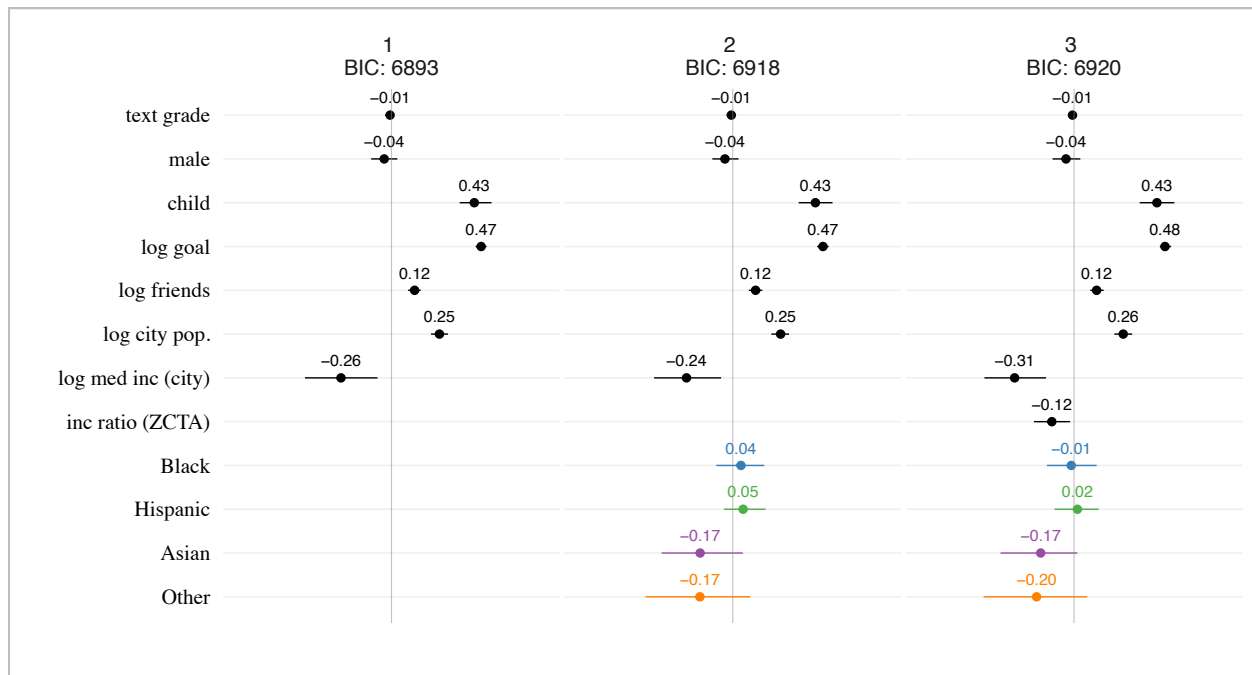


Figure 13: Models for sharing with bootstrap 95% confidence intervals.

Online social network sharing also does not explain differences in returns by race and ethnicity. The models in Figure 13 support Hypothesis 1a: sharing does not vary by race and ethnicity. Model #2, which does not include relative income between groups, shows no differences in sharing by race and ethnicity. The models here do present a striking result that disconfirms Hypothesis 1b, which posited that income levels of potential donors are unrelated to sharing. In fact, *campaigns from areas with lower incomes seem to be shared more than those from areas with high incomes*. Across all models the rate of sharing is *negatively* associated median household income for the location as a whole. Financial capacity of potential donors is represented by two covariates in model #3: the median income of the city, and a ZCTA-based income ratio representing the relative income of a racially-homophilous donor with similar means to the beneficiary. In model #3, both of these covariates have negative

coefficients, indicating that the negative relationship between income and sharing may apply regardless of race and ethnicity.

### Donations: Network Mobilization and Network Financial Capacity

Because network sharing does not seem to vary based on the race and ethnicity of the beneficiary, differences in returns must result from the donations received from potential donors. The conceptual model I present in this paper argues that the number of donations will be a function of the financial capacity of potential donors. The models in Figure 14 allow evaluation of Hypothesis #2, stating that the number of donations is correlated with network financial capacity. These models use median incomes for the race and geographic location of the beneficiary as proxies for network financial capacity. There is some support for Hypothesis 2a, which states that the number of donations is higher in locations with higher income levels. All models show that the number of donations is higher in higher income locations, though the relationship is significant at  $p < .05$  only in model 3. Model 3, which includes an additional income parameter dependent on race and zip code, shows a large and significant association of local income and number of donations. For each 1% rise in median family income for the city, the model predicts a .23% rise in returns. Exponentiating coefficients, Model #2 shows that Black and Hispanic beneficiaries receive roughly 13% and 33% fewer donations than White beneficiaries respectively, keeping other covariates constant. This confirms Hypothesis 2b: the number of donations correlates with patterns of racial income inequality. The result is also consistent with prior research showing lower donation counts for campaigns on behalf of Black recipients and other people of color (Kenworthy et al. 2020). Model 3 provides partial confirmation for Hypothesis 2c: when relative incomes are taken into account, the difference in number of donations disappears for Black beneficiaries. For Hispanic beneficiaries, the number

of donations is also associated with the local financial capacity of Hispanics, but the parameter based on Hispanic ethnicity remains large (decreasing donation counts by  $\exp(.25)$ , or 28%) and highly significant. Additional research will be needed to understand the reason for this deficit.

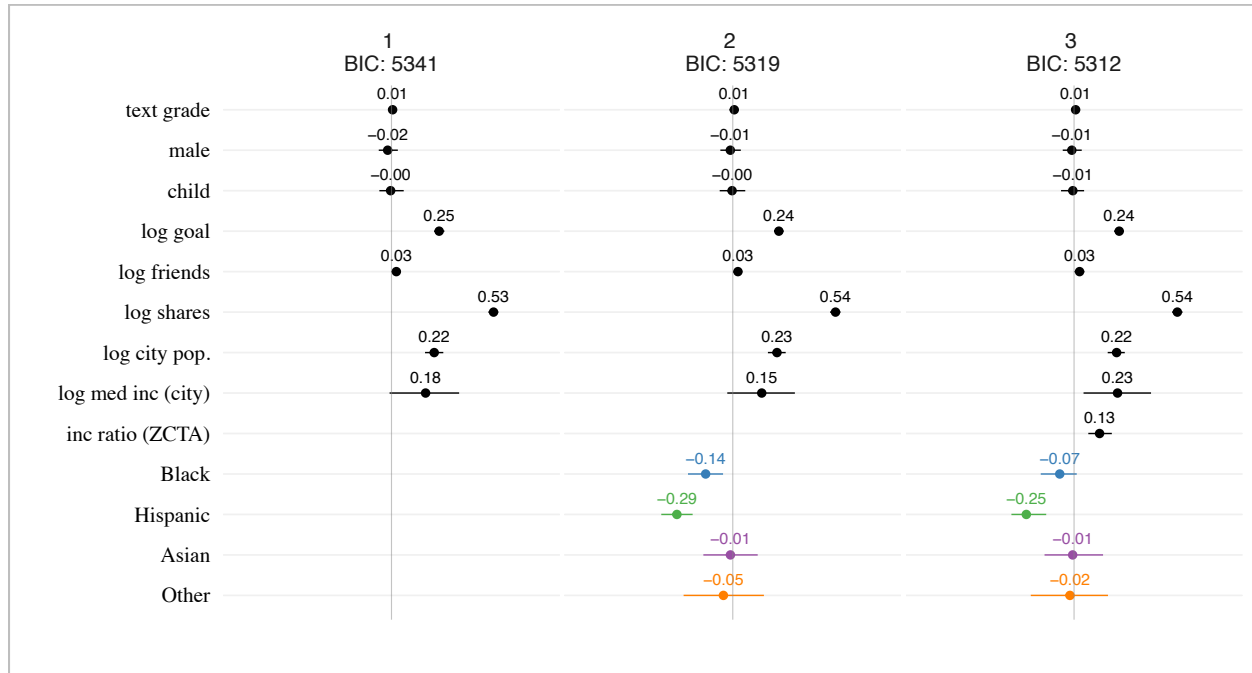


Figure 14 Models for log # of donations with bootstrap 95% confidence intervals

In these models, the primary drivers of the size of the potential donor pool, shares and local population, are strongly associated with additional donations. More sharing translates to more giving. Note that while number of shares is strongly related to outcomes, as would be expected, number of friends of the organizer continues to have a small but significant positive association with number of donations. This lends support for the prediction that closer ties are more likely to donate than more distant ties. Finally, these models show that while campaigns on behalf of children are shared more widely than those on behalf of adults, they do not receive a larger number of donations for each share.

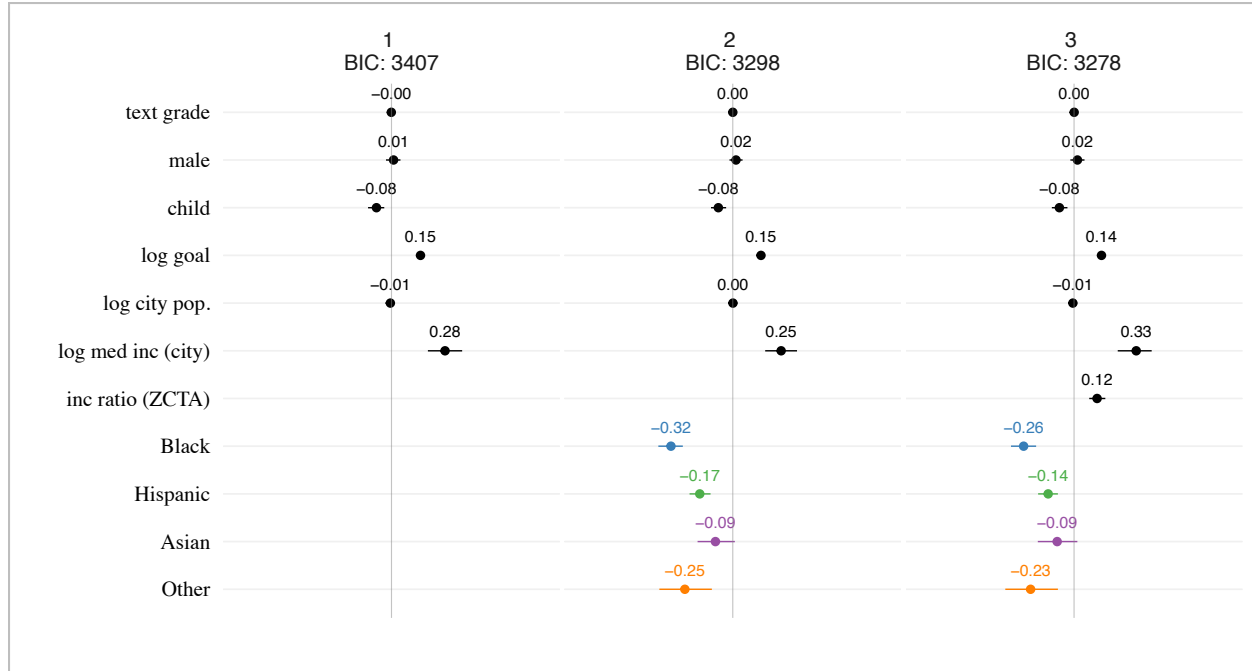


Figure 15: Models for log mean donation with bootstrap 95% confidence intervals

Finally, we turn to the actual amount raised per donation, estimating the log mean donation amount for each campaign. An equivalent model would estimate the log amount raised by the campaign with a covariate for the log number of donations.<sup>7</sup> Figure 15 shows models of mobilization in terms of log mean donation size. These models offer strong support for Hypothesis 3, which argues that the average size of donations is tied to network financial capacity. The local income parameter is positive in all models, confirming Hypothesis 3a: donation size will be higher in locations with higher incomes. Black, Hispanic and “other” race recipients receive lower returns than White and Asian recipients, confirming Hypothesis 3b, which states that donation sizes will, on average, vary with income inequality by race and ethnicity. Hypothesis 3c is confirmed in model 3. Campaign organizer income, as predicted by

<sup>7</sup>  $\log(\text{raised}) = \log(\text{mean\_donation}) + \log(\text{donation\_count})$ .

the race of the beneficiary and the campaign's zip code, appears to be significantly correlated with donation size. As opposed to models of donation counts, including income ratios to account for racial differences in financial capacity shrinks but *does not* eliminate the estimated difference in monetary mobilization for Black beneficiaries. This is also true for Hispanic and "other race" beneficiaries; the changes in money raised are only partially explained by a log-log model including estimated income differentials. Zip-code based income estimates account for 18.8% of the estimated deficit for Black beneficiaries, 21.7% of the deficit for Hispanic beneficiaries and 8.6% for other race beneficiaries.

### Summary of Model Results

In summary, results of these models largely confirm hypotheses that geographic and racial differences in network financial capacity drive a significant proportion of differences in returns by race and ethnicity. The race and ethnicity of the beneficiary is not associated with increased sharing of campaigns, supporting Hypothesis 1a, but network fiscal capacity seems to be *inversely* related to sharing, which is an unexpected result. Hypothesis 2, which argues that network income is a primary driver of the number of donations is also largely confirmed. Citywide income levels are strongly correlated with number of donations. When variation in donor income as predicted by zip code and race of the beneficiary, is taken into account, differences in number of donations for Black beneficiaries are accounted for, though differences for Hispanic beneficiaries remain substantial. Hypothesis 3, which argues that the size of donations also depends on variation in income by race, ethnicity and location is also confirmed. However, very substantial differences in returns remain, even when accounting for income differences in hierarchical models.

The credibility of the models presented here depends on both the applicability of the models and the appropriateness of the data used in these analyses. I estimate the elasticity of number of donations and shares using log-log, hierarchical linear models, with varying intercepts by location. Other modeling choices may be equally valid. More critically, one might question if the model data, in particular the estimation of race and ethnicity of beneficiaries, reflects valid correlates of the perceptions and financial resources of potential donors. In the next section I offer robustness checks for the models and data.

## ROBUSTNESS CHECKS

### Fixed Effect Models

Fixed effect models can include controls to account for location or location-specific median income and population covariates but cannot include both (i.e. fixed effects with dummy variables for cities, cannot be used with independent variables that do not vary by city). I investigated fixed effect models using income and population covariates, which yielded parameter estimates with very similar magnitudes to the mixed-effect models presented above.

### Negative Binomial Models for Count Data

In my primary analyses, I modeled mobilization as the log share counts and log donation counts. I chose to do this because network sharing is an exponential process. However, other studies of crowdsourced medical funding have used Poisson models to estimate counts of inputs (Kenworthy et al. 2020). Overdispersion tests indicate that both share and donation count data in this dataset is severely overdispersed ( $p < .001$ ) and inappropriate for a Poisson model, which assumes equal mean and variance of data (Cameron and Trivedi 1990). Negative binomial models can be used to model count data while providing more flexibility in terms of dispersion. Negative binomial models yielded similar results to the log models presented here, with a

notable difference: the association between citywide median household income and donation count remained positive but was not significant at traditional levels. The association of relative incomes of beneficiaries based on race and ethnicity and the organizer zip-code remained positive and significant.

### Subsets of Data

One important critique of the results presented here is that I personally served as a tiebreaker when raters disagreed about the race, ethnicity or gender of the beneficiary. To assess whether including the possibility that my assignment of race and ethnicity in ambiguous cases affected the results, I ran the analyses including the full set of covariates using only the 1,957 campaigns where two independent raters agreed on the gender and race/ethnicity of the subject. Using this subset of data, results are very similar to those of the models using the whole dataset. The only notable differences were for ‘other’ race beneficiaries, which displayed significant negative coefficient for sharing, and larger drop in donation size in the models using a smaller data set.

### EXAMINING RESIDUAL DIFFERENCES IN RETURNS BY RACE

Models that include covariates that proxy for donor income show that differences in estimated financial capacity likely account for a portion of the inequality in crowdfunding returns by race. However, neither the differences in the number of donations or the size of donations is fully explained by these models. Large and significant coefficients remain. There are several potential explanations for these patterns. First, donation size may not change consistently with respect to available network financial capacity. Second, income ratios used here may underestimate the differences in network financial capacity compared to real world networks. Recall that across all races, organizers were located in ZCTAs that had *higher than average* incomes compared to the city (census place) as a whole. Prior research shows that middle class Black and Hispanic

families are more likely to have poor people in their immediate social networks than middle class Whites (Heflin and Pattillo 2006; O'Brien 2012; Vallejo 2012), so income estimates based on organizer zip codes might overestimate network income for Black and Hispanic beneficiaries. Donation amounts may depend on *wealth* in addition to income, and wealth inequality in the United States is severe. Finally, these data may indicate that potential donors discriminate against Hispanic and Black beneficiaries when choosing to donate, even though there is no apparent discrimination in sharing.

To examine the potential impact of discrimination, I turn to models that estimate the value of individual donations to campaigns, rather than per-campaign aggregates. When analyzing individual donations, models can include surname-based estimates of the probability each donation comes from a *donor* belonging to one of the five ethnic and racial groups in this analysis. These models introduce an additional level of hierarchy, with random intercepts estimated by campaign, nested within a location. Figure 16 shows models predicting log individual donation amounts. Recall that log amounts are used as the dependent variable because individual donations tend to increase in size geometrically. Donors with names likely to be Asian give about the same as donors who are likely to be White (the baseline) and donors who are more likely to be Hispanic and Black give less, independent of the race of the recipient. These differences persist even when proxies for network income are included in the model. The persistence of differences suggests that financial capital available for donations depends on differences in wealth, which is unequal by race and ethnicity, in addition to income. My models do not account for wealth held by potential donors, and it is likely that large donations in particular are made by people with significant financial reserves.

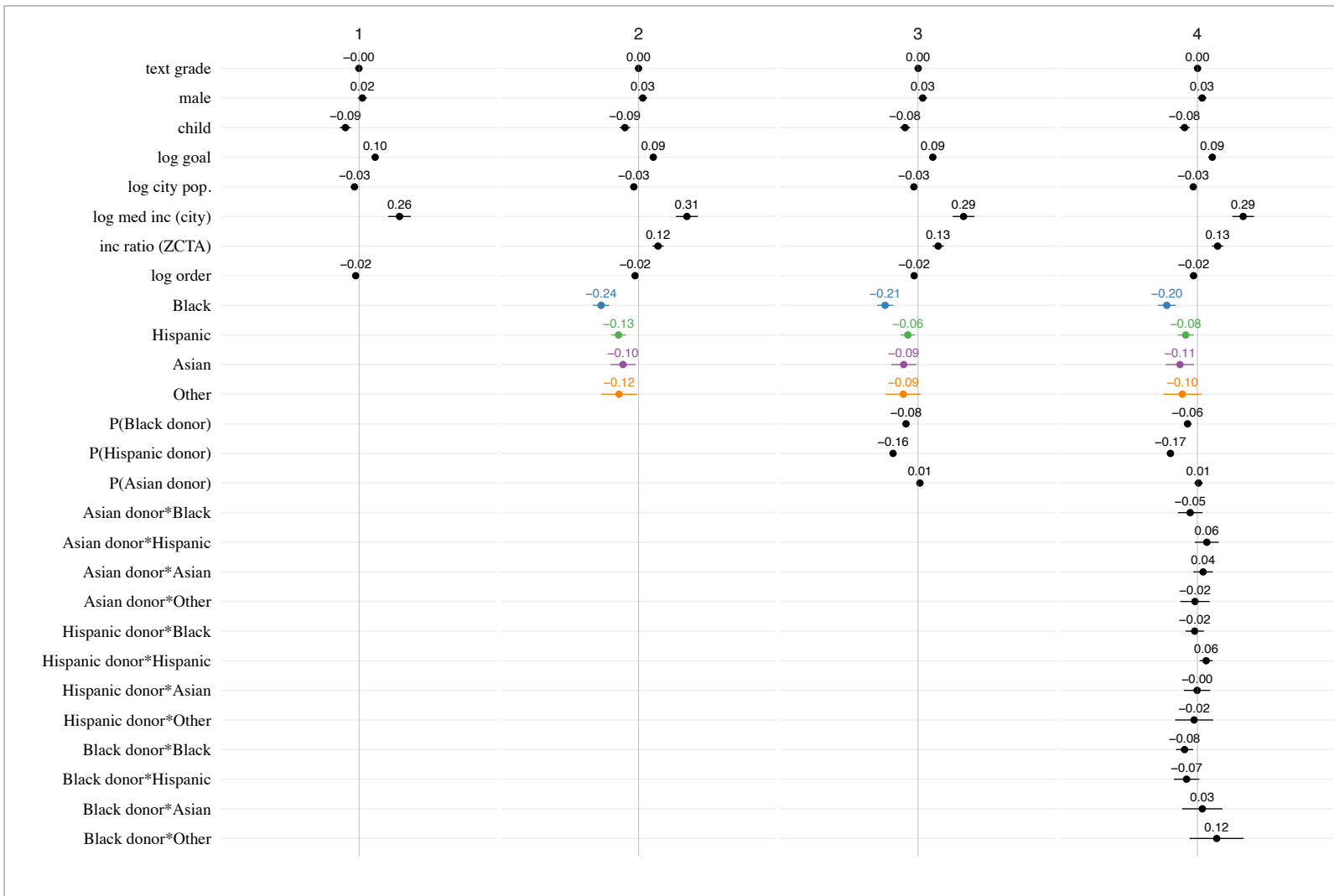


Figure 16 Models predicting log donation size, including estimates of donor race based on surnames.

Models 3 and 4 indicate that Black recipients receive the lowest donation sizes and White recipients the highest, regardless of the race of the donor. In addition to the estimated differences in returns by recipient and donor race and ethnicity, two interactions are significant at a  $p < .05$  level – Black donors on average give *smaller* amounts to Black recipients than they do to non-Black recipients, and Hispanic donors on average give *larger* amounts to Hispanic recipients than they do to non-Hispanic recipients. Figure 17 shows estimates of the expected differences in donation size by the race of the donor and rater-assigned race of recipient, using the full set of covariates in model 4 of Figure 16. I have speculated that one might expect a relatively higher volume of low-value donations for low-income groups making donations to family & close friends, which might explain low average donations shown for Black donors to Black recipients. It is not obvious why these effects would go in the opposite direction for Hispanic donors.

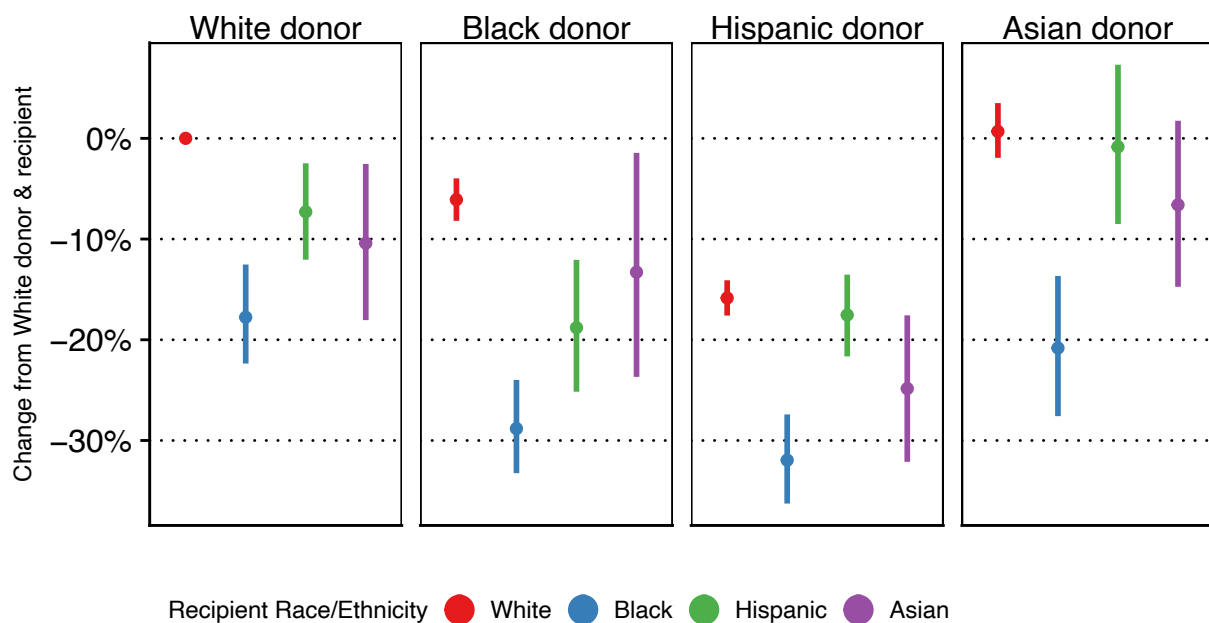


Figure 17: Simulated percent differences in donations size based on surname-based probabilities of donor race, with 95% confidence intervals. Donation size to White recipients is highest regardless of estimated donor race. Donation size to Black recipients is lowest, including donations from donors likely to be Black.

## DISCUSSION

This study establishes that medical crowdfunding replicates inequality through its reliance on social networks that have unequal financial capacity. While many who establish online fundraising campaigns hope their stories will “go viral,” most campaigns spread through networks of family, friends, and friends of friends, and thus the ability to raise funds is constrained by the financial capacity of those in the extended network. The fact that networks demonstrate homophily by geography, race and ethnicity means that, even absent discrimination in donations, crowdfunding replicates inequality. Black and Hispanic crowdfunding beneficiaries find themselves at a particular disadvantage given that current and historical institutional racism has left their communities with the lowest access to financial resources.

I find that *sharing* of campaigns does not seem to be related to the race of the beneficiary. However, I do find that sharing is *inversely* proportional to estimated financial capital in the potential donor network. It is possible that faced with an inability to contribute to a campaign via donation, lower income potential donors help the cause by sharing the campaign instead. Other psychological processes may be in play: lower income donors may feel more empathy for people who face financial difficulty, or high-income donors may feel that only monetary contributions have a meaningful effect on outcomes. More research on decision processes of individual donors would be necessary to understand the reasons for this difference in the behavior of potential donors.

I find that the number of donations to campaigns is correlated with expected financial capacity of the potential donor pool. Citywide income levels are strongly correlated with number of donations. When variation in donor income based on similarity with organizers is taken into account, differences in number of donations for Black beneficiaries are accounted for, though differences for Hispanic beneficiaries remain substantial. Hispanic Americans have bank

accounts and credit cards at slightly higher rates than Blacks, it is unclear why the number of donations to Hispanic campaigns is lower. It is possible that Hispanic donors are less inclined to make public donations, or perhaps are more likely to make in-kind donations in place of monetary donations.

As expected, I find that variations in income by race, ethnicity and location are correlated with donation size. However, very substantial differences in returns by race and ethnicity remain, even when accounting for income differences in expected potential donor networks. Several other factors may drive the relationship between network financial capacity and donation size. Wealth inequality may be an important driver of unequal returns. It also seems likely that the relationship between household income and capital available for donation cannot be completely captured by an elasticity-based model relating log median income to log donation size. It may be that a key determinant is the proportion of the beneficiary's network alters who are just "scraping by" and can spare very little or nothing for donations. Further modeling and simulation may help to identify non-linearities in giving.

The evidence for discrimination by potential donors as a cause of racial disparities is mixed. After accounting for covariates, I find no residual racial or ethnic difference in the frequency with which campaigns are shared, and much of the difference in money raised can be explained by differences in the financial capacity of potential donors. However, even after accounting for campaign features and network financial capacity, Whites receive larger donations from all races and ethnicities and Blacks tend to receive the smallest donations. This pattern of varying degrees of discrimination for different phases of a process brings to mind recent research showing that employment discrimination is more apparent at the job offer stage than at the interview callback stage of the process (Quillian et al. 2020). Similarly, crowdfunding

discrimination may occur for donations, but not for sharing. My estimates of network monetary capacity are necessarily crude, and may not fully capture the differences in access to financial resources caused by past institutional and individual discrimination. Nevertheless, the evidence that all beneficiaries regardless of race give more to White beneficiaries and less to Black beneficiaries is a troubling sign that current discrimination may compound the ongoing impact of past discrimination. Future research should examine inter-racial donations in crowdfunding, perhaps using experimental techniques to establish the impact of beneficiary race on donor decision making.

There are a number of other potential issues with these findings. First, the identification of beneficiary race deserves scrutiny, not least because rating is subjective. Two external raters agreed on the race and ethnicity of beneficiaries only 80% of the time, and I relied on personal judgment to adjudicate the remaining 20% of campaigns. A more reliable mechanism for identifying race and ethnicity could be used, perhaps with more raters and a process that eliminates campaigns with unmatched results. At the same time, many actions in society, for example policing, are affected by these superficial ascriptive properties, so using perceived race as an independent variable has some merit.

Another problem is that the selection of campaigns does not constitute a random sample. GoFundMe is returning a set of campaigns from a query, but their algorithm for returning results is proprietary and non-random. These results should be replicated with an independent set of data sampled from a more complete corpus. I am currently collecting additional data, though because information on the number of online friends is no longer available, future analysis will necessarily concentrate on donations rather than sharing.

A final potential problem is the necessarily crude ways to operationalize the financial capacity of the beneficiary's extended network. Here two measures are used: the income level of the city where the campaign is originated and an estimate of the beneficiary's relative income status in that location based on race of the beneficiary and the organizer's zip code. There is no guarantee that organizers are the same race as the beneficiary or live in the same zip-code, though they almost certainly share strong network ties. Based on the evaluations of online raters, most campaigns are started by the beneficiary or someone in their family, but about thirty percent were started by friends, and raters were unable to determine the relationship for another sixteen percent of the campaigns. Still the size and significance of the effects found with even the crude estimates here indicate that there is a substantial relationship between the measures in these models and network financial capacity in the real world.

Even given these caveats, my findings are important and raise issues that are worthy of further research. The evidence developed here confirms the findings of Kenworthy et al. (2020) and goes further to suggest that race-based differences in GoFundMe may be due to structural issues. Black and Hispanic people in the United States have lower median incomes and less wealth than white people. People who are more likely to be poor (and thus more likely to need help) tend to be tied in networks to other poor people. That the differential outcomes may not be driven by active discrimination should offer no comfort to those with concerns about inequities in the health care system. The results here indicate that improvised responses to inequality, like those provided by GoFundMe, cannot make up for systemic sources of stratification.

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APPENDIX 1: SUMMARY STATISTICS FOR CAMPAIGNS

	White (N=1929)	Black (N=247)	Hispanic (N=321)	Asian (N=81)	Other (N=40)	Total (N=2618)	p value
<b>gender</b>							0.621
Female	1028 (53.3%)	122 (49.4%)	162 (50.5%)	45 (55.6%)	23 (57.5%)	1380 (52.7%)	
Male	901 (46.7%)	125 (50.6%)	159 (49.5%)	36 (44.4%)	17 (42.5%)	1238 (47.3%)	
<b>child</b>							0.476
FALSE	1532 (79.4%)	196 (79.4%)	246 (76.6%)	68 (84.0%)	29 (72.5%)	2071 (79.1%)	
TRUE	397 (20.6%)	51 (20.6%)	75 (23.4%)	13 (16.0%)	11 (27.5%)	547 (20.9%)	
<b>goal</b>							0.010
Median	15000	10000	10000	20000	27500	15000	
Mean (SD)	31282 (48632)	35364 (61519)	28451 (53488)	45845 (72453)	49638 (80970)	32051 (52152)	
Q1, Q3	8000, 35000	5000, 45000	5000, 30000	10000, 50000	10000, 50000	7500, 35000	
<b>friend_count</b>							< 0.001
Median	549	759	541	589	556	565	
Mean (SD)	771 (801)	1234 (1272)	749 (781)	755 (715)	770 (818)	811 (862)	
Q1, Q3	303, 909	382, 1568	282, 920	315, 933	292, 963	305, 960	
<b>shares</b>							0.358
Median	520	528	492	474	557	517	
Mean (SD)	876 (1250)	1022 (1750)	843 (1148)	769 (800)	1020 (1212)	885 (1282)	
Q1, Q3	239, 1081	260, 1038	231, 932	262, 1034	302, 1440	242, 1061	
<b>donation_count</b>							0.003
Median	86	76	65	88	92	83	
Mean (SD)	155 (244)	161 (242)	122 (295)	252 (717)	208 (315)	155 (279)	
Q1, Q3	41, 179	32, 168	28, 132	42, 193	48, 218	38, 171	
<b>raised</b>							< 0.001
Median	7805	4920	4630	7295	8496	7118	
Mean (SD)	14693 (20897)	11315 (16237)	9424 (15125)	19238 (37302)	16952 (22818)	13903 (20720)	
Q1, Q3	3175, 17840	1625, 13628	1800, 10915	3708, 16531	3605, 23450	2778, 16600	
<b>mean_donation</b>							< 0.001
Median	86	61	71	86	82	82	
Mean (SD)	95 (47)	69 (41)	78 (38)	98 (64)	97 (101)	90 (48)	
Q1, Q3	65, 112	43, 86	52, 96	59, 116	59, 102	61, 108	

## APPENDIX 2: COMPARISON OF PLACE AND

The following models use place or CBSA incomes and estimate models using overall household income levels, group-based levels for the geography, or a combination of geography and zip-code based income estimates.

**Log Donations, using Place-based metrics**

	(1)	(2)	(3)
(Intercept)	-6.045 (1.008)	-5.687 (0.934)	-6.926 (1.006)
log_friends	0.027 (0.013)	0.027 (0.013)	0.029 (0.012)
log_shares	0.538 (0.014)	0.539 (0.014)	0.541 (0.014)
log_goal	0.241 (0.013)	0.242 (0.013)	0.237 (0.013)
grade_score	0.008 (0.004)	0.008 (0.004)	0.008 (0.004)
childTRUE	-0.004 (0.032)	-0.004 (0.032)	-0.006 (0.032)
genderMale	-0.013 (0.025)	-0.012 (0.025)	-0.012 (0.025)
log_pop	0.232 (0.024)	0.227 (0.024)	0.223 (0.023)
log_loc_inc	0.152 (0.090)		0.228 (0.090)
race_ethblack	-0.142 (0.045)	-0.071 (0.069)	-0.075 (0.048)
race_ethhispanic	-0.293 (0.042)	-0.247 (0.054)	-0.250 (0.043)
race_ethasian	-0.012 (0.074)	-0.002 (0.074)	-0.007 (0.074)
race_ethother	-0.049 (0.104)	-0.001 (0.108)	-0.021 (0.104)
log_group_inc		0.122 (0.086)	
zip_inc_ratio			0.134 (0.034)
BIC	5319.969	5320.869	5312.896

**Log Donations, using CBSA-based metrics**

	(1)	(2)	(3)
(Intercept)	-8.609 (1.467)	-7.012 (1.350)	-9.185 (1.482)
log_friends	0.033 (0.013)	0.033 (0.013)	0.034 (0.013)
log_shares	0.560 (0.014)	0.560 (0.014)	0.562 (0.014)
log_goal	0.243 (0.013)	0.243 (0.013)	0.238 (0.013)
grade_score	0.007 (0.004)	0.007 (0.004)	0.008 (0.004)
childTRUE	-0.020 (0.032)	-0.020 (0.032)	-0.022 (0.032)
genderMale	-0.005 (0.026)	-0.006 (0.026)	-0.004 (0.026)
log_cbsa_pop	0.180 (0.020)	0.182 (0.021)	0.176 (0.020)
log_cbsa_med_inc	0.404 (0.140)		0.451 (0.141)
race_ethblack	-0.161 (0.045)	-0.020 (0.088)	-0.111 (0.048)
race_ethhispanic	-0.328 (0.042)	-0.231 (0.068)	-0.294 (0.043)
race_ethasian	-0.042 (0.075)	-0.043 (0.075)	-0.043 (0.075)
race_ethother	-0.074 (0.105)	0.041 (0.118)	-0.052 (0.105)
log_cbsa_group_inc		0.253 (0.130)	
zip_cbsa_inc_ratio			0.120 (0.039)
BIC	5348.829	5353.232	5347.281

**Log \$ Raised, using Place-based metrics**

	(1)	(2)	(3)
(Intercept)	0.250 (0.465)	0.997 (0.498)	-0.568 (0.491)
log_goal	0.148 (0.008)	0.149 (0.008)	0.144 (0.008)
grade_score	0.000 (0.003)	0.000 (0.003)	0.001 (0.003)
childTRUE	-0.075 (0.021)	-0.075 (0.022)	-0.077 (0.021)
genderMale	0.017 (0.018)	0.017 (0.018)	0.018 (0.017)
log_pop	0.001 (0.011)	-0.005 (0.012)	-0.006 (0.011)
log_loc_inc	0.253 (0.042)		0.326 (0.044)
race_ethblack	-0.324 (0.030)	-0.221 (0.042)	-0.264 (0.032)
race_ethhispanic	-0.173 (0.028)	-0.105 (0.033)	-0.136 (0.029)
race_ethasian	-0.091 (0.051)	-0.072 (0.051)	-0.088 (0.051)
race_ethother	-0.251 (0.071)	-0.173 (0.073)	-0.228 (0.071)
log_group_inc		0.188 (0.046)	
zip_inc_ratio			0.121 (0.023)
BIC	3298.353	3317.180	3278.563

**Log \$ Raised, using CBSA-based metrics**

	(1)	(2)	(3)
(Intercept)	1.241 (0.755)	1.151 (0.745)	0.452 (0.754)
log_goal	0.153 (0.008)	0.153 (0.008)	0.148 (0.008)
grade_score	0.000 (0.003)	0.000 (0.003)	0.001 (0.003)
childTRUE	-0.076 (0.022)	-0.076 (0.022)	-0.077 (0.021)
genderMale	0.015 (0.018)	0.015 (0.018)	0.016 (0.017)
log_cbsa_pop	-0.021 (0.010)	-0.025 (0.010)	-0.026 (0.010)
log_cbsa_med_inc	0.184 (0.072)		0.249 (0.072)
race_ethblack	-0.328 (0.031)	-0.219 (0.052)	-0.256 (0.032)
race_ethhispanic	-0.167 (0.028)	-0.093 (0.041)	-0.122 (0.029)
race_ethasian	-0.070 (0.051)	-0.073 (0.051)	-0.072 (0.051)
race_ethother	-0.246 (0.072)	-0.160 (0.077)	-0.217 (0.071)
log_cbsa_group_inc		0.196 (0.073)	
zip_cbsa_inc_ratio			0.172 (0.026)
BIC	3330.083	3329.313	3295.339