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INVESTIGATING THE RELATIONSHIP BETWEEN MEDICAL CROWDFUNDING AND PERSONAL BANKRUPTCY IN THE UNITED STATES: EVIDENCE OF A DIGITAL DIVIDE[1]

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As of 2007, an estimated 62% of individual bankruptcy filings in the United States were a direct result of costs borne from medical treatment following illness or injury, up from 46% in 2001. This pressing issue is only getting worse and is in need of relief. In this work, we consider the potential of a relatively recent, and rapidly growing, phenomenon to mitigate the problem: online crowdfunding for medical expenses, wherein patients reach out to their social network for monetary support via online platforms that facilitate the process. On the surface, medical crowdfunding holds the potential to address insurance gaps and to help those burdened by medical debt. However, recent questions have arisen in the healthcare literature around fairness and equity in the distribution of funds. Consistent with the notion of digital divide, many have raised concerns that the individuals most likely to benefit from these services are not the individuals who are most in need. Accordingly, we first seek to establish the effect of this novel phenomenon on a key indicator of financial distress: rates of personal bankruptcy. We then explore heterogeneity in patterns of funding solicitation and acquisition, to assess the presence inequalities across patient populations. We leverage proprietary data from a large medical crowdfunding platform based in the United States, which we combine with county records of personal bankruptcy filings. We report evidence that greater success amongst medical crowdfunding campaigns does translate into a reduction in personal bankruptcy filings. Subsequently, we report analyses which revealed evidence consistent with the presence of a digital divide. Specifically, we report evidence that disadvantaged groups are systematically more likely to launch medical crowdfunding campaigns, yet conditional on campaign launch, garner systematically less in funding. We discuss the implications for the literature on the digital divide, as well as implications for practice and policy.

Keywords: Crowdfunding, medical bankruptcy, online platform, digital divide

Introduction

Crowdfunding is estimated to have facilitated more than U.S. $34 billion in contributions worldwide in 2015. Approximately 20% of all funds contributed via crowdfunding support a social cause. In fact, second only to entrepreneurial ventures, campaigns for social causes are one of the most popular applications of crowdfunding.[2] Despite this, prior research has largely focused on crowdfunding's use in entrepreneurial finance (e.g., Belleflamme et al. 2014; Carvajal et al. 2012; Gaggioli and Riva 2008; Mollick 2014; Schwienbacher and Larralde 2010; Wheat et al. 2013). One particularly unique, yet increasingly prevalent application of crowdfunding, which

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The appendices for this paper are located in the "Online Supplements" section of *MIS Quarterly*'s website (https://misq.org).

[2]Statistics are provided by Crowdfunding Industry Report: http://www.crowdsourcing.org/editorial/global-crowdfunding-market-to-reach-344b-in-2015-predicts-massolutions-2015cf-industry-report/45376.

has yet to receive attention in the academic literature, is for the payment of medical bills, that is, *medical crowdfunding* (Gonzales et al. 2018; Young and Scheinberg 2017).

Medical crowdfunding is an increasingly common campaign category on many leading crowdfunding platforms today. For example, the number of medical-related crowdfunding campaigns on GoFundMe exhibited a seven-fold increase between 2011 and 2014, and its medical campaigns have collectively raised more than U.S. $930 million.[3] Similarly, GiveForward, a medically-focused crowdfunding platform that recently merged with YouCaring, has reportedly raised close to U.S. $200 million for patients,[4] and observed exponential growth following its launch in the summer of 2008.[5] Combined, these medical campaigns represent more than U.S. $1.1 billion in fundraising, a substantial volume even when compared to the best known and largest reward-based crowdfunding platform, Kickstarter, which has enabled more than U.S. $2.7 billion in successful fundraising. Going forward, medical crowdfunding is expected to exhibit a sustained annual growth rate of 25% (Simon 2016).

The dearth of research on medical crowdfunding is noteworthy, given recent calls for research examining the effects of crowdfunding on society and the economy (Agrawal et al. 2014). Medical crowdfunding platforms have the potential to bring about a positive social impact by addressing healthcare insurance gaps and reducing medical bankruptcy in the United States, which has continued to experience persistent increases in healthcare costs. However, for this potential to manifest, these platforms need to benefit the patients who are most in need (i.e., the under- and uninsured, and individuals of low socioeconomic status). Recent editorials and opinions have questioned whether this is in fact the case (Snyder et al. 2017a, 2017b; Young and Scheinberg 2017). Assessments of crowdfunding's economic impacts are thus necessary for formulating appropriate, actionable public policies that can effectively assuage prevailing social and health issues. Moreover, assessments of digital inequality of these services are similarly required. Notably, a related concept, microfinance, has long been touted as a solution to reducing poverty, yet recent research has questioned whether this benefit actually manifests in practice (Angelucci et al. 2013).

In this work, we address the following research questions: *To what degree does success in medical crowdfunding reduce the prevalence of personal bankruptcy? Which patient subpopulations derive greatest (least) benefit from medical crowdfunding?* The use of online crowdfunding platforms to raise funds offers notable advantages over offline efforts. Online fundraisers can achieve much greater awareness and reach, accessing a larger number of potential donors compared to more traditional fundraising avenues. Fundraisers can also engage the crowd to share their story, to advocate on their behalf, thereby bringing forth additional funds from outside the beneficiary's immediate social circle. In this regard, crowdfunding platforms serve as a coordinating mechanism, offering a technology-enabled tool to support individuals in the fundraising process. However, it is also important to consider recent work on Kickstarter, which observed that increased awareness of crowdfunding in recent years has led to commensurate increases in the volumes of "frivolous" (Geva et al. 2017) and fraudulent (Cumming et al. 2016) campaigns. In medical crowdfunding, individuals may (1) exaggerate their financial needs by overstating fundraising goals, (2) launch unjustified campaigns, or (3) engage in "fake" fundraisers. Numerous reports of the latter have appeared in the media, and the CEO of GoFundMe has recently acknowledged that individuals continue to exploit the service for illicit personal gain (e.g., raising money on behalf of family members without their knowledge).[6] Such behaviors put the bankruptcy alleviating effect of medical crowdfunding into question. Moreover, recent work on loan-based crowdfunding has offered evidence that access to such services can actually *increase* personal bankruptcy rates (Wang and Overby 2017). This occurs because awareness of a seemingly easily accessible capital source causes individuals to become less conscientious in their financial decisions. Thus, it is imperative to systematically assess and quantify this new online phenomenon, to better understand its actual impact in alleviating the financial distress of patients.

Moreover, understanding heterogeneity in the impact of online phenomena on various subpopulations is of equal, if not greater importance (Chan et al. 2016; Chan and Wang 2018; Greenwood and Agarwal 2015). As noted above, recent academic work has raised concerns that medical crowdfunding may not benefit the individuals who need it most. This concern arises from the argument that the individuals most likely to execute a successful crowdfunding campaign are potentially those who are better educated, tech savvy, have the means and flexibility to oversee an online

[3]See https://www.nerdwallet.com/blog/loans/medical-debt-crowdfunding-bankruptcy/ and http://whotv.com/2015/03/14/gofundme-sees-boom-in-medically-related-fundraising-campaigns/.

[4]https://finance.yahoo.com/news/youcaring-acquires-giveforward-expand-reach-140000098.html.

[5]See Appendix A, Figure A1, for a plot of the exponential growth in campaign launch volumes over time in our sample of GiveForward data.

[6]http://www.huffingtonpost.com/andre-bourque/is-crowdfunding-your-medi_b_7088486.html.

fundraiser, and who have a large pool of accessible, potential donors, notions consistent with the digital divide literature (Bonfadelli 2002; Di Maggio et al. 2004; Hargittai and Hinnant 2008).

To explore these questions, we leverage proprietary data on medical-related donations made via one of the largest medical crowdfunding platforms in the United States, between August 2008 and April 2012. We combine information on fund-raising activities with county-level data on personal bank-ruptcy filings by quarter, and a series of demographic and socioeconomic controls. We separately consider the influence of fundraising on counts of Chapter 7 and Chapter 13 bank-ruptcy filings, which respectively differ in terms of whether the debt is fully discharged or is instead simply restructured and subject to a scheduled repayment plan (more detail provided on this in the next section). To account for unob-servable sources of heterogeneity, we employ a random coefficient model characterized by county random intercepts and slopes, along with year and quarter fixed effects. We also consider the robustness of our results in various ways; we explore a secondary model that utilizes a combination of county, year, and quarter fixed effects, as well as an instru-mental variable approach, based on a unique set of instru-ments that exploit features specific to the crowdfunding platform (GiveForward.com), namely exogenous geographic and inter-temporal variation in the supply of campaign coaching services provided by the platform operator.

Our study provides evidence that crowdfunding activity on GiveForward reduced the rate of personal bankruptcy in the United States over our period of observation. We estimate that a 10% increase in funds raised by medical crowdfunding campaigns translated to a 0.04% decline in the volume of personal bankruptcies. More concretely, our estimates sug-gest that for every $1,207 raised on GiveForward, approxi-mately one bankruptcy was eliminated. Perhaps most importantly, when we consider heterogeneity in who posts campaigns and who raises funds, we find clear asymmetries. While we observe that disadvantaged populations are signifi-cantly more likely to engage in medical crowdfunding, we also find that the benefits of medical crowdfunding accrue systematically less to these populations, conditional on con-ducting a campaign. These findings lend credence to the recent concerns raised in the healthcare literature about a digital divide around medical crowdfunding, in terms of need versus benefit (Snyder et al. 2017a, 2017b; Young and Scheinberg 2017).

Our work contributes both to theory and practice. First, from an academic perspective, our study builds on a number of streams of literature, including that on the subject of crowd-funding and its societal impacts (Agrawal et al. 2014; Burtch et al. 2013) as well as that dealing more broadly with the impact of online technologies on social outcomes (Bhuller et al. 2013; Chan and Ghose 2014; Chan et al. 2016; Chan et al. 2018). As this novel IT-based phenomenon permeates various aspects of social and economic activity, there is a growing need to better understand how it affects society, and to quantify its impact. Additionally, our study contributes to the heath IT literature, responding to recent calls to assess how digital solutions can reduce treatment costs and improve healthcare outcomes (Agarwal et al. 2010; Fichman et al. 2011).

Our work builds on the digital divide literature by arguing previously under-considered sources of digital inequality. The platform-based, two-sided nature of online crowdfunding, and the communication-rich nature of the context (i.e., that fundraisers must craft polished, persuasive pitches to solicit funds from peers), are unique aspects that distinguish our study context from settings considered in prior work on the digital divide (Robinson et al. 2015). Our work thus speaks to additional, novel sources of digital inequality. Specifically, with respect to the platform nature of medical crowdfunding, minority (traditionally disadvantaged) groups are likely to experience a relatively weaker network effect on two-sided digital platforms, a pattern jointly attributable to minority groups' typically smaller scale of participation in digital markets and participants' general preference for homophilous transaction partners. Consequently, despite having access and use, digital inequality may nonetheless continue to manifest on such platforms, due to a lack of critical mass in the number of potential transaction partners (donors in the case of crowd-funding). Our work thus builds on other recent literature, which has documented evidence of reduced benefits among minority populations on digital platforms (Edelman et al. 2017; Ge et al. 2016). Additionally, with respect to the need for persuasive, polished communication via digital media, disadvantaged groups are likely to face greater difficulties crafting such communications, and thus may have a harder time converting peers into transaction partners.

Finally, from a practical standpoint, in validating and quanti-fying the impact of medical crowdfunding on the rate of personal bankruptcy, our study informs stakeholders of the potential of crowdfunding when it comes to addressing unmet healthcare costs and insurance gaps. Our study also sheds light on the underlying mechanisms, providing insights on the degree to which medical crowdfunding benefits specific segments of the population, so that actionable policies can be made to enhance this new digital financing platform.

Background and Context

Medical Bankruptcy and Unmet Healthcare Costs

Healthcare costs continue to rise in the United States, and this is an issue of great concern for many reasons. It has long been established that individuals' likelihood of pursuing medical treatment is decreasing in the cost of that treatment (Currie and Gruber 1996; Manning et al. 1987). These costs are particularly high for individuals who lack health insurance.[7] Prior research indicates that, even among those individuals who hold some form of health insurance, in many cases the coverage is insufficient. In fact, nearly 75% of medical debtors *do* hold some form of health insurance (Himmelstein et al. 2009). For individuals who lack insurance, or who have insufficient coverage, the personal cost of seeking medical treatment can be quite high. This is notable, because failure to seek treatment, which is directly tied to cost, is reportedly associated with more than 40,000 deaths in the United States each year (Wilper et al. 2009). Despite the extent and importance of medical bankruptcy, the empirical health policy literature has remained relatively silent on the topic thus far, largely due to a lack of access to comprehensive bankruptcy data (Himmelstein et al. 2005).

The issue of medical bankruptcy is not just one of mortality; there are also financial implications. When individuals seek treatment, healthcare providers often bear the initial cost. This is because hospitals are legally required to provide immediate treatment to any patient in need, without regard for compensation. Although hospitals seek to reclaim these costs from the patient after the fact, they are frequently unsuccessful in this effort, particularly when patients file for personal bankruptcy (Gross et al. 2014).

Unmet treatment costs thus drive large fiscal losses for healthcare providers each year. Unpaid medical bills accounted for approximately $30 billion in losses for U.S. healthcare providers in 2005 (Gruber 2008), and this number has likely only grown of late, given the more recent prevalence of personal bankruptcy. Indeed, prior work indicates that, as of 2007, more than 60% of all personal bankruptcy filings in the United States were a direct result of costs borne due to medical treatment (Himmelstein et al. 2009), an approximate 50% increase from 2001 (Himmelstein et al. 2005).

There are two main types of bankruptcy that individuals may pursue when faced with fiscal pressure from medical debts. Chapter 7 bankruptcy allows for the discharge of all unsecured debt (e.g., credit cards, utility fees and medical bills). However, to qualify for Chapter 7 bankruptcy, an individual must pass a "means test"; that is, the net value of their assets and income must fall below a defined threshold.[8] If a debtor fails to pass the means test, he or she may only file under Chapter 13, which allows for debt restructuring through repayment plans (Livshits et al. 2007). Approximately 70% of all personal bankruptcy filings in the United States are filed under Chapter 7, with the remaining 30% filed under Chapter 13. Bearing the above in mind, our analyses consider both Chapter 7 and Chapter 13 bankruptcy filings.

It is useful here to consider the consumer bankruptcy decision and the scenarios under which bankruptcy will most likely arise. Personal bankruptcy is typically sought when it offers the individual a net financial benefit (Fay et al. 2002). This depends, in turn, on a number of factors, including individual liquidity, wealth, debt, the immediate cost of bankruptcy filing, such as legal and court fees, and the proportion of liquid wealth that is lost through filing—accounting for bankruptcy exemptions around certain assets, such as real estate (Gross et al. 2014).[9] Individuals will opt to file for bankruptcy when their net financial position, conditional on bankruptcy filing, exceeds the position they would retain without bankruptcy filing. Put simply, if an individual could locate a source of funds that could improve his or her financial position, then the probability of bankruptcy filing would be reduced.

It is important to consider that consumers may file for bankruptcy "strategically," and not as a last resort to deal with unanticipated financial shocks. Strategic filing refers to consumers who determine their present level of debt based on expectations about a future financial shock and the bankruptcy option. In contrast, a nonstrategic filer is someone who incurs debt myopically, without consideration for possible bankruptcy filing (i.e., with an honest intention of paying off the debt) (Zhang et al. 2015). In 2005, Congress passed the Bankruptcy Abuse and Prevention and Consumer Protection Act (BAPCA), intended to curb abuse of the bankruptcy system. Zhang et al. (2015) empirically examined the efficacy of that legislation, reporting strong evidence that consumers are not strategic in their filing behavior following the Act's passage.

[7] A Gallup poll conducted in late 2014 indicates that approximately 13.4% of the American population remains uninsured (http://www.gallup.com/poll/178100/uninsured-rate-holds.aspx; accessed January 2015).

[8] The Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) requires individuals to have a monthly income lower than the median income of their state to be able to file under Chapter 7.

[9] In referring to "wealth" we mean net financial position, which may in fact be negative in the presence of debt.

Although bankruptcy has the benefit of eliminating or reducing pressure from credit collection agencies, it also has downsides. Access to credit is severely reduced following a bankruptcy declaration. There are also social costs, because individuals may experience anxiety or shame. There are also many forms of debt that cannot be discharged via bankruptcy, and, though it may be a beneficial recourse for patients, it forces healthcare providers to absorb unmet costs. If an approach could be identified that allows patients to meet treatment costs while avoiding bankruptcy filings, this would enhance social welfare and likely be preferred.

Medical Crowdfunding

The crowdfunding model presents a novel solution to short term fiscal pressure faced by individuals from the costs of medical treatment. Crowdfunding platforms initially arose as online avenues via which individuals could tap the crowd to raise the capital necessary to pursue projects, business ideas, and ventures. There are multiple variants of crowdfunding, with the primary differentiator being the presence and nature of incentives offered to contributors. Typical forms of crowdfunding include reward-based, lending-based, donation-based and equity-based models (Burtch et al. 2014). Recently, crowdfunding has been adapted to fundraising for medical expenses. Medical fundraising typically takes place on donation-based crowdfunding platforms, where no material incentive is offered to contributors. A prominent example of a platform enabling this type of crowdfunding is GoFundMe. Despite the preponderance of medical crowdfunding activity, not much is known about its socioeconomic impact, including the degree to which it influences personal medical bankruptcy. Although intuition might suggest a clear positive impact, the relationship between crowdfunding and bankruptcy rates is potentially quite nuanced (Wang and Overby 2017).

Medical crowdfunding websites are online platforms, facilitating fundraising on the part of patients who solicit donations from the crowd. These websites digitally disintermediate the fundraising process and are characterized by significant network effects (Parker and Van Alstyne 2005). Medical crowdfunding is thus likely to alleviate the financial needs of patients over and above traditional fundraising channels in several ways. First, by acting as the focal point for matching willing donors to beneficiaries in need of financial assistance (Bailey and Bakos 1997), the crowdfunding platform greatly enhances beneficiaries' ability to solicit donations from others by aggregating prospective donors in a single place, eliminating offline spatial and temporal constraints in capital acquisition (Agrawal et al. 2015; Sorenson et al. 2016). Face-to-face solicitation is difficult to scale, and even more so when one considers the medical conditions of beneficiaries and the financial constraints they bear.

Second, the information sharing features of crowdfunding platforms have the dual effect of increasing the quantity and speed of fundraising. Not only does the site allow calls for donation to be simultaneously broadcast to a patients' immediate network of family and friends, it also allows this information to be shared via social media, which enables a Matthew effect (Merton 1957), wherein information propagation accelerates by orders of magnitude as second- and third-order social connections spread the word (Bakshy et al. 2012; Mollick 2014). Consequently, the pool of potential donors tends to surpass those accessed via traditional fundraising avenues, because distant relatives, acquaintances, and even strangers may become donors. Third, given that crowdfunding works through the pooling of financial resources across groups of people, each donor can give a small amount of money and still aid the beneficiary. With a smaller cost of contribution, individuals become more likely to contribute (Meer 2014). Thus, even individuals with weak ties to the beneficiary may donate, thereby again expanding the pool of prospective donors beyond what would be available in offline settings.

Although the overall crowdfunding movement has generally been viewed as successful by democratizing capital access for entrepreneurs (Sorenson et al. 2016), recent work has reported evidence that loan-based crowdfunding can actually increase rates of personal bankruptcy (Wang and Overby 2017). This can happen because awareness of seemingly easy access to a novel source of capital may lead people to be less conscientious in their financial decisions, driving them deeper in debt. Additionally, with regard to medical crowdfunding in particular, recent questions have been raised by the medical community about equity and fairness in patient access (Snyder et al. 2017a, 2017b; Young and Scheinberg 2017), that is, a digital divide.

The digital divide refers to various types of social inequality in Internet access and use (Agarwal et al. 2009; Hargittai and Hinnant 2008; Loges and Jung 2001; Shah et al. 2001). In terms of usage, individuals with higher education and income levels are more likely to possess the prerequisite online experience and skills to utilize the Internet in ways that can enhance their financial and social capital. The ability to search online can influence the kind of material one finds on the web, thereby contributing to a "knowledge gap" (Bonfadelli 2002), which can in turn influence welfare. It has been shown that individuals with greater education and income are more likely to use the Internet for capital-enhancing purposes, including news seeking, retrieving financial and health information, researching products, looking for jobs, or using the

Internet for work-related purposes (Boyce and Rainie 2002; Hargittai and Hinnant 2008; Madden 2003). Crowdfunding platforms are a relatively new online phenomenon. As such, they are likely to draw participation from portions of the population that are tech savvy and more highly educated (Mossberger et al. 2003).[10]

While past work on digital inequality has largely focused on the roles of access, use, and self-perceptions (Robinson et al. 2015), the crowdfunding context brings in new considerations that could also lead to disparate outcomes among different populations, conditional on use. First, many online platforms are multi-sided in nature, and a user's derivation of benefit is highly reliant on participation by a critical mass of potential transaction partners. In our context, fundraising by a patient is highly dependent on the willingness and ability of his or her social circle to contribute toward the campaign. As such, despite enabling greater access and coordination in fundraising, a digital divide may nonetheless manifest on medical crowdfunding platforms because the size of participating populations that hold high socioeconomic status are likely to be larger, and such groups are in a better position to provide funds. Moreover, success in the crowdfunding context is likely to have an increased reliance on the fund seeker's access to advanced education. This is because advanced education helps individuals develop their ability to articulate polished written messages (Bereiter and Scardamalia 1987; Kellogg 2008), which is often necessary to effectively elicit trust and to persuade other individuals to contribute toward a patient's treatment costs. Given this rationale, medical crowdfunding may tend to offer a systematically outsized benefit to individuals who belong to advantaged populations, and who are highly educated or have the financial means to access higher education.

Past work on reward-based crowdfunding also notes that, on average, most fundraising campaigns perform quite poorly. The bulk of fundraising success is typically attributable to a small proportion of blockbuster campaigns, with a long tail of relative failures (Agrawal et al. 2014, 2015).[11] The donation-based nature of medical crowdfunding can compound this issue because, unlike reward-, equity-, or loan-based crowdfunding, donation-based (medical) crowdfunding offers donors no tangible returns. This implies that medical crowdfunding outcomes may ultimately depend heavily on the financial support provided by beneficiaries' direct family members and friends (Basu and Meltzer 2005; Jacobson 2000). Indeed, the reward- and loan-based crowdfunding literature is replete with evidence that a large portion of campaign contributions arrive from personal social connections, such as friends and family (Agrawal et al. 2015; Burtch et al. 2018; Liu et al. 2015; Kuppuswamy and Bayus 2015). This implies that the benefits of medical crowdfunding may be most likely to accrue to individuals who have preexisting, sizable online social networks (Mollick 2014). Being bestowed with a social circle of well-to-do connections can further enhance the success of one's crowdfunding efforts. In this sense, crowdfunding sites may simply serve as an alternative channel for financial activity that would have simply taken place via other channels, had the platform not been present.

Finally, if the benefits of medical crowdfunding were to accrue on the basis of social network size and connections, racial minorities within the country might systematically benefit less from the platform, given that their numerical representation is lower to begin with, and that the bulk of an individual's social capital (and thus fundraising potential) derives from same-race social connections (James 2000).[12] In this regard, even when individuals from historically disadvantaged minority groups, or of low socioeconomic status, gain access and attempt to make use of crowdfunding platforms, they may nonetheless obtain asymmetrically lower benefits, if they enjoy a weaker network effect than do larger groups. Consistent with this notion, recent studies have documented evidence of discriminatory behavior on other multisided platforms, such as those for home sharing (Edelman et al. 2017) and ridesharing (Ge et al. 2016). Because smaller racial groups are less likely to identify candidates for same-race connections, they may face hurdles identifying and soliciting interested donors, potentially preventing them from reaping the full benefits of medical crowdfunding. Given much of the value of medical crowdfunding platforms depends on their efficacy as a search, solicitation, and coordination tool, this can lead to another form of digital divide.

Beyond concerns related to a digital divide, another possible issue is that medical crowdfunding could lead to moral hazard and adverse selection. As awareness of medical crowdfunding increases and the massive success of viral fundraisers receive media coverage, individuals may be attracted by the potential of soliciting seemingly "free" money (Geva et al. 2016). These individuals may post fraudulent campaigns (Cumming et al. 2016) or they simply exaggerate their finan-

[10]For instance, Quantcast reports that 59% of visitors to GiveForward.com are college or university educated (https://www.quantcast.com/giveforward.com/demographics).

[11]For instance, less than 1% of the campaigns on Sellaband account for over 70% of funds raised and 10% of successfully funded projects on Kickstarter account for 63% of funds.

[12]For instance, African Americans only constitute 12.9% of the U.S. population.

cial needs. If campaigns are fraudulent or if they misrepresent patients' financial situations, any money raised would be unlikely to translate directly into bankruptcy reductions. As noted above, anecdotal reports speak to individuals' misuse of medical crowdfunding platforms (e.g., lying about their illnesses, creating fake campaigns for genuinely ill friends or relatives, and using funds for purposes other than those listed in the campaign description) (Snyder 2017a, 2017b). While crowdfunding sites do not encourage users to mislead potential donors and typically forbid misinformation in their terms of use, platform operators do frequently encourage users to utilize language that generates "empathy" among prospective donors and to "inspire" individuals who are viewing their campaign page (Snyder 2017a, 2017b). If a sufficiently high proportion of campaigns are in fact fraudulent, exaggerated, or initiated by individuals who are not at real risk of bankruptcy, successful fundraising on crowdfunding platforms would be unlikely to have a beneficial influence on bankruptcy rates.

In sum, while anecdotal evidence speaks to individuals raising large volumes of money on medical crowdfunding sites (Sifferlin 2012), suggesting that medical crowdfunding holds a clear potential to reduce financial burdens amongst patients, there are numerous factors that may preclude the full-scale manifestation of these beneficial effects. As such, it is important to quantify the strength of the relationship in a rigorous, systematic manner, and to understand which subpopulations benefit most (or least) from these services.

Methods

Study Context and Data

We begin with an assessment of the relationship between medical crowdfunding activity and personal bankruptcy filings. Subsequently, we go on to explore the digital divide, assessing heterogeneity in use and fundraising benefits derived from medical crowdfunding by different subpopulations.

Our main dependent variables in the baseline analysis capture the total volumes of Chapter 7 and Chapter 13 personal bankruptcy filings in each county and quarter, as reported by the federal judicial center.[13] The use of aggregate data is common in empirical studies of bankruptcy (e.g., Buckley and Brinig 1998; Gross and Notowidigdo 2011) because accurate data on individual-level filing is generally not available. Studies that rely on disaggregated bankruptcy data typically employ voluntary surveys of specific population segments. Such data sources are known to suffer from serious selection and reporting biases that can create estimation problems, leading to misleading results. Thus, official bankruptcy data at a county level is superior in that they do not suffer from misreporting issues and provide a complete picture of bankruptcy incidence.

It is well established that one's propensity to file for bankruptcy is dependent on geography, because local culture and norms heavily influence perceptions of the stigma associated with bankruptcy filing (Lefgren and McIntyre 2009). Moreover, the administration and practice of bankruptcy law also varies by geography, which can create heterogeneous incentives and disincentives for bankruptcy filing (Braucher 1993; Sullivan et al 1989). Measuring bankruptcy levels at the county level allows us to observe and account for any location-specific variation.

We consider medical crowdfunding activity at *GiveForward.com*[14] between the third quarter of 2008 and the second quarter of 2012, inclusive. GiveForward.com was one of the largest medical crowdfunding website in the United States during our period of study, having raised more than $175 million toward various health-related causes, most of which pertained to the payment of patients' medical expenses.[15] Other causes supported by the platform included memorial and funeral costs, disaster relief, and pet medical expenses. Unlike many reward-based crowdfunding sites, such as Kickstarter, which employ a provision point mechanism (i.e., funds are only released to the campaign organizers if the fundraising target is met), GiveForward employed a flexible fundraising scheme, wherein they would disburse all donations to beneficiaries, regardless of the amount raised.

We model personal bankruptcy rates as a function of medical crowdfunding activity in the same location. We construct a novel panel dataset, combining county-level bankruptcy data,[16] with proprietary data on donations that was supplied by GiveForward. Given that medical bankruptcies are largely filed as Chapter 7 and Chapter 13 personal bankruptcies, our outcome of interest is the count of such filings. It is worth

[13]Federal Judicial Center Website: https://www.fjc.gov/research/idb/bankruptcy-cases-filed-terminated-and-pending-fy-2008-present. Note, repeating our analyses on an alternative source of data, namely that provided by the RAND Corporation, yields similar results, which are available upon request.

[14]GiveForward was subsequently acquired by YouCaring, which was subsequently acquired, in turn, by GoFundMe.

[15]GiveForward makes explicit mention of how crowdfunding can aid patients in financial distress, helping them to avoid bankruptcy (http://www.giveforward.com/p/medical-bankruptcy).

[16]The dataset captures all bankruptcy filings made in fiscal years, on or after October 2007.

acknowledging that our measure of bankruptcy filings includes both medical and nonmedical bankruptcies (i.e., individuals who pursue bankruptcy for other reasons). Although we would prefer to limit our analysis to medical-bankruptcy filings, a national repository of bankruptcy cases categorized by the cause of filing is not readily available (Himmelstein et al. 2005). Debtors' reluctance to discuss their bankruptcy motivations has made it difficult to collect accurate survey data to proxy for the frequency of medical bankruptcies. In particular, prior research indicates that only 50% of bankruptcy filers actually admit to it in surveys (Fay et al. 2002). However, the fact that our dependent variable includes nonmedical bankruptcies is not cause for particular concern, because this constitutes measurement error in our dependent variable. Unlike measurement error in independent variables, which may produce biased estimates, measurement error in dependent variables merely inflates standard errors and reduces model fit, making it more difficult to detect statistically significant relationships (Greene 2003).[17]

Our key independent variable captures crowdfunding activity on GiveForward, with a particular focus on fundraisers for medical expenses. For each fundraiser, we have data on (1) the geographic location of the beneficiary, (2) the dollar amount solicited and raised, (3) the duration of the fundraiser, (4) the type of fundraiser, and (5) a textual description of the fundraiser's purpose. Based on this information, we construct an absolute measure of crowdfunding activity, *Log(Amount Raised)*, which reflects the total dollars contributed to medical crowdfunding campaigns in a given county-quarter. Because funds are paid out to beneficiaries only after the completion of the campaign, this variable reflects all fundraising activity associated with campaigns in a county that were completed in the associated period.

We combine the data on bankruptcy and crowdfunding activity with a set of demographic, socioeconomic and health-related controls. These indicators are included as covariates to account for time varying local factors that may influence the incidence of bankruptcy filings in each county over time. First, the age distribution in a county is likely to influence the prevalence of bankruptcy filings. For example, Jacoby et al. (2001) report that nearly half of debtors aged 65 and over have quoted medical reasons for filing bankruptcy. Further, being responsible for supporting the financial needs of the young and elderly, the ratio of the working-age group to the dependent group is indicative of the average financial pressures faced by the population in a geographic location. Racial composition in a location is also likely to affect the rate of bankruptcy filings, because racial gaps in incarceration rates, divorce, and the incidence of single-parent families can undermine access to credit and financial resources (Berkowitz and Hynes 1999; Dickerson 2004; Domowitz and Sartain 1999). In addition to these demographic factors, we account for population size in each county, as this reflects an upper bound on the potential population of bankruptcy filers.

We further control for socioeconomic indicators that are known to influence bankruptcy levels (i.e., median household income and poverty levels) (Gropp et al. 1997; Gross and Souleles 2002). Given that impoverished and low-income populations do not have substantial financial resources to pay for unanticipated medical expenses and recurring bills, they are more prone to medical bankruptcy when met with treatment needs. Moreover, since poverty-stricken areas may be more successful in attracting financial relief from assistance programs, we consider quadratic terms for poverty to account for possible nonlinear effects. Another socioeconomic indicator that needs to be controlled for is the number of loans taken for home mortgages. Zhu (2011) observes that a home purchase represents a large personal expenditure and the acquisition of a large debt, resulting in a positive relationship between the home ownership and bankruptcy.

Health insurance reduces the out-of-pocket expenses paid for medical treatment (Gross and Notowidigdo 2011), which can in turn insulate patients from medical bankruptcy. Yet, some studies only find a modest decrease (or no decrease) in medical bankruptcies accompanying an expansion in insurance coverage (Finkelstein et al. 2012; Himmelstein et al. 2011). These inconclusive findings on the benefits of medical insurance might be a result of a nonlinear impact of insurance coverage, wherein the bankruptcy alleviating effects of health insurance only set in after coverage reaches a certain threshold. To account for such effects, we control for Medicaid and Medicare coverage across county-quarters, including both the raw levels as well as quadratic terms. In addition, we control for the joint impact of these two insurance schemes by including their interaction. Finally, we account the number of Medicare patients who have sought primary care services, to proxy for the size of the population that is actively incurring medical costs.

Our measures of age, race, household income, poverty levels, and population size are obtained from the U.S. Census Bureau, and home mortgage loan data is retrieved from the Federal Housing Finance Agency. Measures of Medicaid coverage are derived from the Small Area Health Insurance Estimates from the U.S. Census, while Medicare coverage and utilization is provided by the Dartmouth Atlas of Healthcare. Descriptive statistics for our variables are provided in Table 1.

[17]Nevertheless, we include falsification tests and additional checks to provide additional assurance that the use of all personal bankruptcy filings does not undermine the validity of our main analyses.

Table 1. Descriptive Statistics

Variable Name	Observations	Mean	Std. Dev.	Min	Max
Outcome Variables					
Log (No. of Nonbusiness Chapter 7 Filings)	3,770	5.084	1.678	0.000	10.207
No. of Nonbusiness Chapter 7 Filings	3,770	581.126	1466.046	0.000	27082.000
Log (No. of Nonbusiness Chapter 13 Filings)	3,770	4.934	1.808	0.000	9.573
No. of Nonbusiness Chapter 13 Filings	3,770	503.280	1068.010	0.000	14364.000
Log (No. of Business Chapter 7 Filings)	3,770	2.237	1.562	0.000	7.249
No. of Business Chapter 7 Filings	3,770	29.901	76.643	0.000	1406.000
Log (No. of Business Chapter 13 Filings)	3,770	0.841	1.108	0.000	4.727
No. of Business Chapter 13 Filings	3,770	3.934	8.455	0.000	112.000
Independent Variables and Covariates					
Log (Amount Raised)	3,770	4.359	3.555	0.000	12.649
Amount Raised	3,770	2401.572	8839.069	0.000	311507.000
Fraction Raised	3,697	0.154	0.274	0.000	2.748
Log (No. of Fundraisers)	3,770	1.005	0.500	0.693	4.554
No. of Fundraisers	3,770	2.311	3.847	1.000	94.000
Ages 25 to 64 Proportion	3,770	0.526	0.030	0.360	0.667
Ages 65 & Above Proportion	3,770	0.138	0.040	0.059	0.492
African American Proportion	3,770	0.117	0.133	0.001	0.816
Asian Proportion	3,770	0.035	0.049	0.001	0.443
Hawaiian/Native American Proportion	3,770	0.015	0.040	0.001	0.769
Log (Population Size)	3,770	12.143	1.396	6.744	16.113
Log (Median Household Income)	3,770	10.813	0.248	10.012	11.706
Log (No. of People in Poverty)	3,770	10.185	1.410	5.283	14.443
Log (No. of Home Mortgage Loans)	3,770	1.603	2.933	0.000	10.391
Population Prop. under Medicaid Coverage	3,770	83.237	5.165	61.400	95.500
Population Prop. under Medicare Coverage	3,770	0.086	0.039	0.003	0.330
Log (Medicare Enrollees with Primary Care Visit)	3,770	4.376	0.086	3.076	4.555
Log (Cost of Medicare program)	3,770	19.018	1.302	14.390	22.819
Log (Cost of Hospice Services)	3,757	15.550	1.432	0.000	18.926
Log (No. of Patients Using Hospital In-Patient Services)	3,770	8.222	1.236	3.401	11.766
Log (No. of Emergency Department Visits)	3,770	9.463	1.211	4.554	12.850
Prop. of Patients using Skilled Nursing Facilities	3,766	5.008	1.167	0.840	10.290

Econometric Specifications

As noted above, our analysis relates medical crowdfunding activity at GiveForward to the volume of bankruptcy filings in a county, i, and year-quarter, t. Our outcomes of interest are the number of Chapter 7 and Chapter 13 personal bankruptcy filings. We estimate a random coefficient model, based on the following considerations. Temporal heterogeneity is likely to be present because past work has noted that the adoption of bankruptcy exemption laws in various locations has affected the prevalence of strategic bankruptcy filings (Agarwal et al. 2003; Shepard 1984). Moreover, exogenous temporal shocks, such as the implementation of government policies that influence bankruptcy (e.g., tax breaks) and variation in business cycles, can introduce systematic shifts to bankruptcy levels across different time periods. As such, we include year and quarter fixed effects in our model specifications.

Scholars have also noted significant differences in the prevalence of bankruptcy across state lines that are not explained by socioeconomic status or other such measurable factors

(Lefgren and McIntyre 2009). Accordingly, it has been suggested that these differences may be attributable to the variation in cultural acceptability of bankruptcy across geographic regions. Cultural norms of this sort are effectively intangible, and are therefore difficult to measure directly. A sensible approach to account for this variation is to specify a model with location-specific random intercepts, such that counties can vary from one another in terms of their baseline bankruptcy levels. In addition to varying intercepts, counties may differ from one another in terms of their bankruptcy trajectories over time. Depending on the local policies and culture, these trajectories may be flat (i.e., no change over time), they may be systematically increasing or decreasing over time, and they may be linear or curvilinear in form. Thus, we further relax the assumption that counties share a common slope (i.e., parallel regression lines) by allowing each county's regression line to have its own slope over the years.

This setup is equivalent to a growth-curve model that allows for the estimation of intercounty variability in intracounty patterns of change over time (Curran et al. 2010). The proposed random coefficient model is more flexible compared to traditional longitudinal models and is characterized by higher levels of statistical power, particularly compared to modeling approaches that require equal numbers of repeated observations for all counties (Muthén and Curran 1997). The modeling approach we take has been widely adopted in practice to capture idiosyncratic effects in longitudinal data (Rabe-Hesketh and Skrondal 2008).

We include the number of GiveForward medical fundraisers conducted in each county, in each quarter, as an additional control, because the magnitude of fundraising outcomes will naturally depend on the volume of campaigns soliciting money. By controlling for this factor, our main variable of interest captures the effect of each additional dollar raised on personal bankruptcy, conditional on the number of fundraisers.[18] Finally, to enforce temporal precedence and account for the fact that bankruptcy filings tend to happen after some delay, we lag our measures of crowdfunding activity by one period (note, we subsequently consider an instrumental variable strategy to address potential endogeneity in its various forms). Given that both the dependent and independent variables have skewed distributions and can vary widely across locations, it is more meaningful to understand the impact that crowdfunding has on bankruptcy in terms of percentage change. As such, we estimate a log-log specification presented in Equation 1.

$$\begin{aligned}\log\left(1+Bankruptcies_{it}\right) &= \beta_1+\beta_2\log\left(1+AmountRaised_{it-1}\right)\\ &+\beta_3\log\left(1+Fundraisers_{it-1}\right)\\ &+\alpha X_{iy}+\gamma_y+\mu_q+\zeta_{1i}+\zeta_{2i}Y_y+\varepsilon_{it}\end{aligned} \quad (1)$$

Here, counties are indexed by i, year-quarters by t, years by y (where $y \in$ 2008, 2009, 2010, 2011, 2012), and quarters by q (where $q \in$ 1, 2, 3, 4). Additionally, X_{iy} is the vector of annual county-level characteristics described earlier. The remaining terms, γ_y and μ_q, capture the year and quarter fixed effects, respectively. Finally, ζ_{1i} is the random intercept for each county and Y_y is the corresponding random coefficient for each year. Our primary parameter of interest is β_2, which reflects the effect of fundraising dollars at GiveForward on the logged volume of personal bankruptcy filings. To assess the sensitivity of the coefficients to alternative specifications, we estimate a variety of other models, described in detail in the following section. We first rely on a random coefficient model that includes county, year, and quarter fixed effects. We then consider a straightforward fixed effect specification, incorporating fixed effects for time and counties. Finally, we consider an equivalent specification employing a negative binomial estimator, to account for the overdispersion in our outcome measure, number of bankruptcy filings.

Additional Empirical Checks

Robustness Checks

We consider a series of alternative model specifications and variable operationalizations, to assess the stability of our results. First, there could be nonlinear effects from the control variables that might affect the estimation of the coefficients associated with our fundraising variables. As described earlier, poverty levels, along with utilization rates of Medicaid and Medicare, could have higher order effects on medical bankruptcy rates. We include the quadratic terms of these factors in our model specification to assess sensitivity.

Second, sudden illnesses, accidents, and chronic conditions can induce unexpected, severe, or persistent financial pressure on patients, which can in turn lead to medical bankruptcies. The prevalence of sudden and long-term medical needs across locations and time may not be fully captured by our existing set of controls. As such, we include additional variables that indicate the type of healthcare utilization and spending for

[18] A subtle, but important point is worth noting here about the interpretation of the main regressor, *Log(Amount Raised)*. Our regression setup implies that the coefficient associated with fundraising activity reflects increases in the total amount of money raised, while the number of fundraisers is held constant. Thus, the coefficient will approximate the average effect on bankruptcy volumes from increases in the success of crowdfunding campaigns.

Medicare beneficiaries.[19] Third, we include a variety of interaction terms between our location-based controls and the number of active medical fundraisers, to account for nonlinear trends in medical crowdfunding use stemming from differences in demographics, socioeconomic status, and health-related measures across locations and time. Fourth, we account for nonlinear effects of socioeconomic indicators on bankruptcy by incorporating interaction terms between poverty and key demographic variables.

Finally, we construct an alternative measure of crowdfunding activity representing the ratio of funds raised to funds solicited, *Fraction Raised*, in each county, for a given quarter, to supplement our absolute measure of fundraising outcomes. This fractional measure reflects the relative success of crowdfunding campaigns in a location, at a point in time. However, we note that the amount solicited by crowdfunding campaigns might not always be representative of the beneficiaries' financial needs.[20] Accordingly, this fractional measure is likely to be a rather noisy indicator of crowdfunding success. Given its relative (normalized) nature, the coefficient associated with the *Fraction Raised* is also more difficult to interpret.[21] Nonetheless, it remains useful for the purposes of comparison.[22]

Endogeneity Concerns

In addition to the above robustness checks, we consider the possibility that contribution activity on GiveForward may be endogenous with respect to bankruptcy rates. A statistically significant relationship between fundraising activity at GiveForward and the rate of bankruptcy filing in a county might result from spurious, unobserved factors. For example, donation activity at GiveForward might be correlated with other unobserved forms of fundraising activity and philanthropy (e.g., other crowdfunding sites, access to credit and lending, or traditional charitable organizations).

To account for these issues, we sought a set of exogenous instrumental variables, correlated with *Log*(*Amount Raised)*, yet uncorrelated with the error term, e_{it}. One such instrument pertains to GiveForward's provision of personalized campaign coaching services, first introduced in 2010, and gradually increased through 2012.[23] GiveForward's fundraising coaches provided personalized advice to campaign organizers, to aid them in realizing better fundraising outcomes. We employ the amount of money solicited specifically by coached campaigns, in a given county and quarter, as an instrument for actual fundraising outcomes, because both the act of coaching and the specified fundraising target would have a material impact on the actual dollar amount raised, yet, for reasons articulated below, should be uncorrelated with any unobserved features of the individual raising money, or features of the location in which they reside.[24] Figure 1 depicts a scatter plot of the log of funds raised and the log amount solicited by coached campaigns. The plot overlays a linear trend, which indicates a strong positive correlation between the endogenous variable and the instrument.

This instrument is likely to satisfy the exclusion restriction for the following reasons. First, the launch of coaching services was not a competitive decision on the part of the platform.[25]

[19]These covariates include patient's cost of utilizing Medicare programs, patient's cost of hospice services, number of beneficiaries using hospital inpatient services, number of emergency department visits, and the proportion of beneficiaries using skilled nursing facilities. Details of these measures are available at https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/medicare-geographic-variation/gv_puf.html.

[20]From our data, there is great variance in the amount of money solicited across campaigns, even within a common disease type or category (see Appendix B, Figure B1). For instance, users have solicited between $0 and $250,000 for breast cancer campaigns in our data. Moreover, a substantial number of campaigns have asked for $0 or $1, and simply stated that "any amount helps" in their description.

[21]The fractional measure does not capture the actual volume of crowdfunding activity. To illustrate, the fractional measure cannot differentiate a county-quarter with one fully funded campaign that has a $500 goal from a county-quarter with ten fully funded campaigns each having a $5,000 goal. Both county-quarters would have the same values under the fractional measure (i.e., 1), while the crowdfunding volume in the latter case would have a more meaningful impact on alleviating bankruptcy risks. Thus, it is more useful to consider the raw volume of amount raised to arrive at a holistic view of crowdfunding's impact.

[22]Given that the *Fraction Raised* variable is calculated based on the number of fundraisers, we do not include the Number of Fundraisers as a covariate in this specification, because it leads to issues of multicollinearity.

[23]GiveForward initially offered coaching services to a very small number of campaigns in 2010, although the bulk of the roll-out did not take place until 2011.

[24]As mentioned earlier, the amount solicited does not correlate directly with the actual financial needs of beneficiaries. We consider this aspect to be helpful in fulfilling the requirements of an instrumental variable, since the amount solicited correlates with the endogenous variable, yet is not directly linked to the bankruptcy risk of users. We formally assess the exclusion restriction assumption of the instrument empirically.

[25]Coaching services are in line with GiveForward's prosocial goal of helping individuals find funding for their treatment. Indeed, an analysis of Google Search trends comparing GiveForward with terms representing other prominent medical crowdfunding platforms (i.e., YouCaring and GoFundMe), during the same period, indicates that GiveForward did not face substantial competition in this space until well after coaches were first introduced.

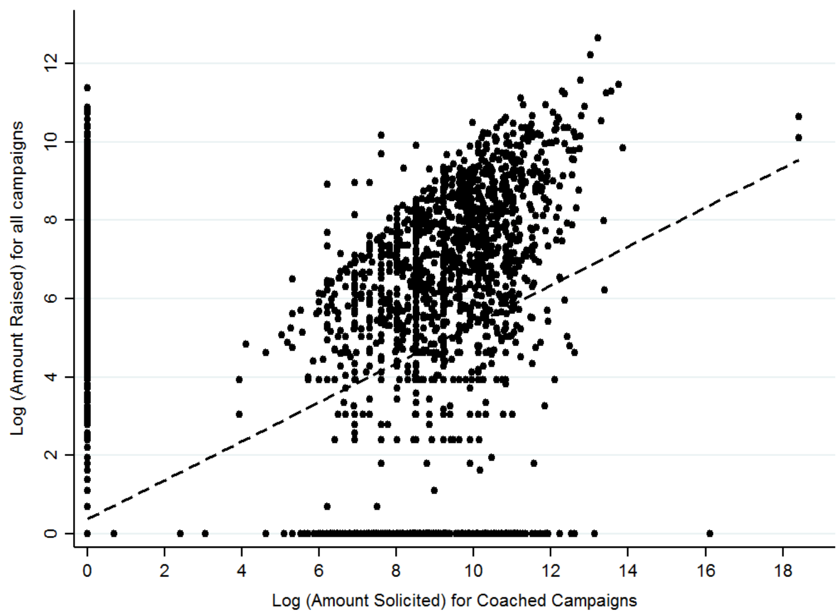

Figure 1. Relationship Between Amount Raised and Fraction of Coached Campaigns

Second, personalized campaign coaches were a feature unique to GiveForward,[26] which implies that the instrument is unlikely to correlate systematically with unobservable effects in the local economy, such as changes in the general volume of charitable activity, crowdfunding activity on other crowdfunding platforms, or beneficiaries' social network characteristics. Third, coaches are a shared service delivered virtually on GiveForward, thus coaches were not systematically assigned to any given geography during our period of study. As GiveForward increased the supply of coaches over time, the proportion of campaigns receiving a coach increased as well. Thus, exogenous variation in the supply of coaches (and their quasi-random assignment), implies that the proportion of coached campaigns does not differ systematically between counties. Finally, and most importantly, based on our interviews with GiveForward executives, coaches were not systematically assigned based on any rule or strategy during this initial roll-out period. This claim is supported in the data as well; through a regression analysis, we find that conditional on the volume of fundraisers,[27] neither the amount raised nor the amount solicited in past periods significantly associates with the subsequent volume of campaigns coached in a county. Thus, the assignment process of coaches to fundraisers appears uncorrelated with campaign, location or individual characteristics.[28]

We also consider the lag of fraction raised as an instrument. This instrument is based on logic akin to that articulated by studies that have employed lagged prices as instruments for contemporaneous prices (e.g., Villas-Boas and Winer 1999, p. 1327). The success of prior crowdfunding campaigns is unlikely to correlate with unobserved local economic conditions or the characteristics of beneficiaries seeking funds in the present period. In particular, the county fixed effects present in our specification control for any common demand shocks that might be correlated over time. Moreover, the concern that bankruptcies from a previous period might spill over into a later period is also unlikely, because of time limits that apply to the discharge of bankruptcy, which makes it highly undesirable to file for multiple bankruptcies within a short period of time.

[26]GiveForward claims to be the only crowdfunding site that provides its users with personalized coaching (http://www.giveforward.com/blog/fundraising coaching).

[27]Certain locations can predominantly have more fundraisers due to greater general awareness of the GiveForward platform. With a larger volume of fundraisers from these locations, the chance of having coaches assigned to fundraisers from these counties will naturally increase. Hence, we added the number of fundraisers as a control.

[28]GiveForward coaches were generally assigned in an *ad hoc* manner during our period of observation, subject to availability. Although all campaigns now automatically receive a coach, coaches were not broadly available in our study period. As such, we take advantage of exogenous variation in the *supply* of coaches, in aggregate, which was a function of GiveForward's recruiting and hiring process, as well as variation in the volume of active campaigns.

At the same time, prior campaign success is likely to correlate with the success of subsequent campaigns in a location, for various reasons. On the one hand, prior campaign success may increase awareness and perceived credibility of Give Forward among the local population, thereby bringing forth more donors and increasing the amount raised in subsequent periods. On the other hand, donors who have given in previous periods may be less inclined to give to subsequent campaigns, due to a budget constraint (i.e., crowding out).

As a final instrument, we consider the number of fundraisers launched in a county, as a proportion of the overall number of GiveForward fundraisers initiated in the same period, across the United States. As with our lagged fraction raised instrument, the proportion of fundraisers in a county is likely to be correlated with the amount raised for reasons related to increased awareness of the platform, as well as the shared budget constraint of the local donor pool (i.e., crowding out). Further, controlling for any macro-economic shocks via time fixed effects, the total number of fundraisers that are initiated across the rest of the country is unlikely to correlate with local bankruptcy trends in a focal county, because micro-level conditions affecting bankruptcy vary widely across counties.

Falsification Tests and Face Validity

We further check whether the relationship between crowdfunding activity and bankruptcy filing arises spuriously, in three ways. We begin by conducting two tests that assess whether the relationship is driven by location or temporal trends. We then consider the results of a survey we conducted with campaign organizers raising funds on Give Forward, to assess face validity of the results gleaned from our econometric analyses.

In our first test, we replace our personal bankruptcy filing outcome with the volume of business bankruptcy filings. A significant coefficient in this estimation would be cause for concern, because it would suggest that there are omitted factors driving the main results. In such a case, it is plausible that extraneous factors such as improvements to prevailing economic and business conditions (known to drive business bankruptcies) are simultaneously increasing crowdfunding success and reducing personal bankruptcy rates, leading to the false sense that the reduction in bankruptcy level is a result of the donations received from GiveForward. This falsification test also serves as a check for whether the presence of non-medical bankruptcy filings in our outcome variable can drive the result. A significant coefficient in this test would imply that our measure of crowdfunding activity is somehow associated with nonmedical bankruptcies (i.e., business-related bankruptcies). Thus, this falsification check sheds light on whether our observed estimates are indeed reflective of the effect of crowdfunding activity on medical bankruptcies.

Next, we perform a permutation test, again to assess whether the main results arise spuriously. We randomly reassign values of our key independent variables (amount raised and number of fundraisers) across observations in the panel, in three ways, and estimate our main model specification on the resulting data with the expectation of observing null results. In each of our three "shuffling" approaches, we repeat the shuffle-estimation process 100 times, and we recover the average estimates and standard errors for both variables. The first shuffling approach is a naïve method, wherein we reassign the amount raised and number of fundraisers, without preserving the location or sequencing information from the original data. A null result in this approach helps demonstrate that the results we observe are likely to be dependent on the combination of timing and location in which crowdfunding activity actually emerged.

Next, we preserve the timing and sequence of observations in the data as amount raised and fundraisers conducted are shuffled; that is, we only randomly reassign panels across locations. In doing so, a null result would suggest that the observed negative relationship between bankruptcies and fundraising is dependent on the specific location in which fundraising has been observed. That is, macro-economic conditions across the United States cannot explain our main findings.

Finally, as a third check, we identified the counties that did not have any GiveForward campaigns during the study period, and overlaid the amount raised and number of fundraisers (with preserved order) on the bankruptcy levels of these counties. Once again, we do so expecting to observe a null result. A significant negative coefficient on amount raised in this analysis would reveal that our crowdfunding variables are correlated with extraneous variables that are simultaneously related to bankruptcy filing behavior, implying a spurious relationship.

Following these falsification tests, we assess the face validity of our econometric results using first-hand data, collected via a survey of GiveForward campaign organizers. With the assistance of GiveForward, we surveyed a random sample of campaign organizers, soliciting information on the dollar amount of their medical costs, the degree to which the funds they raised ultimately helped them to avoid bankruptcy, and details about any insurance coverage the beneficiary held. We then measured the crowdfunding success of beneficiaries and their self-reported tendency toward filing for medical-related bankruptcy, as a point of comparison for our econometric results. This analysis provides additional confidence that the effect of crowdfunding on bankruptcies does in fact come from the alleviation of financial burdens associated with medical expenses.

Baseline Results

We begin by reporting the results from our main specification in Table 2. We do so for Chapters 7 and 13 bankruptcy filings separately. The results for each chapter were reported for random coefficient, fixed effects, and negative binomial specifications. In Models 1 to 5, we estimate the relationship between amount raised on GiveForward and the number of nonbusiness Chapter 7, controlling for the number of fundraisers, demographic and socioeconomic factors, coverage and utilization of Medicaid and Medicare programs, and the number of home mortgage loans taken. In these models, the main variable of interest, *Log*(*AmountRaised)*, is not significant. In Models 6 to 10, we repeat the same analysis using Chapter 13 bankruptcies as the dependent variable. These models produce negative and significant coefficients for the *Log(AmountRaised)* variable. These results seem reasonable when we consider the nature of the different types of bankruptcy. As noted earlier, Chapter 7 bankruptcy is only available to individuals who lack the means to repay creditors. Accordingly, individuals who do not meet those conditions (i.e., individuals with an income source for repayment) will need to file for bankruptcy under Chapter 13. Given that the Chapter 7 filers are able to completely discharge their debt through their bankruptcy status, they do not have an incentive to seek additional financial resources. Conversely, individuals who are unable to pass the means test for Chapter 7 bankruptcy would likely be motivated to seek alternative financial sources (i.e., crowdfunding), to avoid filing for Chapter 13 bankruptcy. This is because, while Chapter 13 bankruptcy formulates a repayment plan for its filers, the affected individuals would still need to commit their future earnings to debt repayment. Moreover, the stigma and damage to one's credit rating associated with bankruptcy filing would continue to apply.

The results for the Chapter 13 bankruptcies are robust in models where we apply clustered standard errors (Models 7 and 9). In our random coefficient model (Model 7), we see that conditional on the volume of GiveForward campaigns, a 10% increase in funds raised is associated with 0.04% fewer bankruptcies in a county, on average, in the subsequent quarter. Interpreted more concretely, the random coefficient estimates from Model 7 (Table 2) indicate that approximately $1,207 raised translates to one less bankruptcy filing. In a recent study, Zhu (2011) contrasts the financial characteristics of bankrupt households with average non-bankrupt households and finds that the typical bankrupt household holds $1,615 in medical debt, whereas the average non-bankrupt household holds $944 in medical debt, a difference of $671 (equivalent to $795 in 2010 dollars).[29] This descriptive difference suggests that a typical household with excessive medical debt could avoid bankruptcy if it manages to receive financial aid in excess of $795. Domowitz and Sartain (1999) find that medical debt greater than 2% of household income can create a tangible positive impact on the likelihood of bankruptcy filing. Based on calculations using median household income and accounting for inflation, this translates to $1,201 in 2010 dollars, which suggests a lower bound on medical debt that can induce bankruptcy filing. Intuitively, this amount would be effective in alleviating the bankruptcy risks for households that hold medical debt amounts that fall near the lower bound zone, as established in Domowitz and Sartain. Notably, our estimate of $1,207 is greater than the minimum amount of financial relief ($795) needed to shift an average at-risk household away from bankruptcy as reported by those authors. Taken together, these comparisons suggest that our estimated effects are plausible.

The regression results also reveal other relationships of interest. Consistent with the three main model specifications, the proportion of working individuals (aged 25 to 64) is positively related to bankruptcy, whereas median income is negatively related with bankruptcy, although it is not precisely measured. We also note a positive link in the number of primary care visits and Chapter 13 bankruptcy levels, which agrees with the intuition that medical-related expenses can increase the financial burden of a population.

Robustness Checks and Addressing Endogeneity

Having seen that medical crowdfunding has an effect on Chapter 13 bankruptcy filings, we next focus on assessing the robustness of that result.[30] First, we consider the inclusion of quadratic controls. In Model 1 of Table 3, we find that the funds raised on GiveForward continue to hold a negative association with bankruptcy rates when squared terms are included. Second, we assess the sensitivity of the results with respect to additional healthcare utilization controls. In Model 2, the addition of these covariates does not qualitatively affect the main results. In Models 3 and 4, where additional interaction terms related to fundraisers and poverty are included, we observe that *Log(Amount Raised)* still consistently holds negative and significant coefficients.

[29] We picked 2010 as it is the midpoint of our data.

[30] When the same set of robustness checks are performed on Chapter 7 bankruptcies, the estimates for amount raised are qualitatively similar to that derived in Table 2.

Table 2. Relationship Between Amount Raised and Bankruptcy Types

	Chapter 7 Bankruptcies					Chapter 13 Bankruptcies				
	Random Coefficient		Fixed Effects		Neg. Bino.	Random Coefficient		Fixed Effects		Neg. Bino.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log (Amount Raised)$_{t-1}$	-0.0001	-0.0001	-0.0000	-0.0000	0.0002	-0.0044**	-0.0044**	-0.0039**	-0.0039*	-0.0028**
	(0.0011)	(0.0012)	(0.0011)	(0.0013)	(0.0010)	(0.0018)	(0.0021)	(0.0020)	(0.0023)	(0.0012)
Log (No. of Fundraisers)$_{t-1}$	0.0148	0.0148	0.0109	0.0109	0.0170*	0.0293*	0.0293*	0.0194	0.0194	0.0158
	(0.0100)	(0.0093)	(0.0101)	(0.0094)	(0.0090)	(0.0167)	(0.0152)	(0.0175)	(0.0168)	(0.0109)
Demographic Controls										
Ages 25 to 64 Proportion	1.9018***	1.9018***	-0.5880	-0.5880	2.5168***	3.6712***	3.6712***	4.7996**	4.7996*	4.1814***
	(0.5532)	(0.6092)	(1.2865)	(1.2156)	(0.6668)	(0.8186)	(1.0089)	(2.2271)	(2.7987)	(0.8168)
Ages 65 & Above Proportion	0.7620	0.7620	-4.6601**	-4.6601	0.8008	-0.9889	-0.9889	0.4306	0.4306	-1.0013
	(0.5679)	(0.6364)	(2.1340)	(3.3545)	(0.7211)	(0.8424)	(0.8368)	(3.6943)	(4.5474)	(0.8413)
African American Proportion	-1.2302***	-1.2302***	-2.1819	-2.1819	-1.1366***	2.7260***	2.7260***	4.7864*	4.7864	2.7041***
	(0.1424)	(0.1733)	(1.6251)	(1.6434)	(0.1580)	(0.2052)	(0.2082)	(2.8132)	(3.4868)	(0.2081)
Asian Proportion	-1.1483**	-1.1483**	1.7223	1.7223	-2.2280***	-2.6298***	-2.6298***	7.7678*	7.7678	-2.7291***
	(0.5787)	(0.5026)	(2.4248)	(2.3209)	(0.5961)	(0.8292)	(0.9069)	(4.1976)	(4.7933)	(0.8877)
Hawaiian/Native American Proportion	-1.1972***	-1.1972***	-2.4049	-2.4049	-1.2464***	-2.8004***	-2.8004***	-12.6138	-12.6138	-3.6209***
	(0.3520)	(0.3315)	(5.2183)	(3.8651)	(0.4197)	(0.5076)	(0.6370)	(9.0336)	(8.1576)	(0.6081)
Log (Population Size)	1.0788***	1.0788***	-0.1972	-0.1972	1.0505***	1.0667***	1.0667***	1.7509***	1.7509**	1.0766***
	(0.0649)	(0.0792)	(0.3755)	(0.4172)	(0.1272)	(0.1082)	(0.1152)	(0.6501)	(0.7566)	(0.0851)
Socioeconomic Controls										
Log (Median Household Income)	-0.1584	-0.1584	-0.1115	-0.1115	-0.2318	-0.0627	-0.0627	-0.3819	-0.3819	-0.1249
	(0.1151)	(0.1238)	(0.1578)	(0.1854)	(0.1951)	(0.1868)	(0.2006)	(0.2731)	(0.3683)	(0.1533)
Log (No. of People in Poverty)	0.0144	0.0144	-0.0282	-0.0282	0.0945	-0.0043	-0.0043	-0.0030	-0.0030	-0.0004
	(0.0604)	(0.0743)	(0.0649)	(0.0837)	(0.1206)	(0.1015)	(0.1089)	(0.1123)	(0.1327)	(0.0780)
Log (No. of Home Mortgage Loans)	0.0003	0.0003	-0.0000	-0.0000	-0.0073*	-0.0008	-0.0008	0.0011	0.0011	-0.0005
	(0.0013)	(0.0011)	(0.0013)	(0.0011)	(0.0038)	(0.0023)	(0.0020)	(0.0022)	(0.0020)	(0.0017)
Medical-Related Controls										
Prop. under Medicaid Coverage	0.0183***	0.0183***	0.0102	0.0102	0.0051	-0.0101	-0.0101	-0.0033	-0.0033	-0.0080
	(0.0047)	(0.0057)	(0.0069)	(0.0078)	(0.0095)	(0.0074)	(0.0074)	(0.0119)	(0.0113)	(0.0069)
Prop. under Medicare Coverage	-8.2077***	-8.2077***	-5.7228*	-5.7228	-26.8845***	-3.2245	-3.2245	-5.4284	-5.4284	-2.0949
	(3.0355)	(3.1380)	(3.4619)	(3.5632)	(7.3804)	(4.7940)	(4.5865)	(5.9930)	(5.6528)	(4.5379)
Medicaid Coverage × Medicare Coverage	0.0963***	0.0963***	0.0646	0.0646	0.3313***	0.0125	0.0125	0.0440	0.0440	-0.0066
	(0.0364)	(0.0369)	(0.0418)	(0.0429)	(0.0873)	(0.0573)	(0.0555)	(0.0723)	(0.0711)	(0.0544)
Log (Medicare Enrollees with Primary Care Visit)	-0.0118	-0.0118	0.6769**	0.6769*	-0.4543**	0.8719***	0.8719***	0.6588	0.6588	1.0358***
	(0.1488)	(0.1591)	(0.2666)	(0.3850)	(0.1911)	(0.2261)	(0.2689)	(0.4616)	(0.7209)	(0.2387)
Clustered Standard Errors		✓		✓			✓		✓	
Number of Observations	3770	3770	3770	3770	3770	3770	3770	3770	3770	3770

Notes: Dependent variables for Models 1-4 and 6-9 are the logged counts of respective bankruptcy filings, while that for Models 5 and 10 are the non-logged counts of the respective bankruptcy filings. The main regressor, Log(Amount Raised), is lagged by one quarter. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Table 3. Robustness Checks and IV Model

	Random Coefficient Model				IV Regression
	(1)	(2)	(3)	(4)	(5)
Log (Amount Raised)$_{t-1}$	-0.0044**	-0.0049**	-0.0049**	-0.0049**	-0.0232**
	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0112)
Log (No. of Fundraisers)$_{t-1}$	0.0311**	0.0314**	-0.2925	-0.4217	-0.4709
	(0.0153)	(0.0152)	(0.7289)	(0.7334)	(0.8990)
Demographic Controls					
Ages 25 to 64 Proportion	3.6089***	4.0272***	4.4640***	18.6896***	-13.9939
	(1.0221)	(1.0214)	(1.0674)	(6.4145)	(34.2396)
Ages 65 and Above Proportion	-0.8163	-0.8843	-0.5612	-0.5758	6.7021
	(0.8468)	(0.8125)	(0.9092)	(0.9011)	(9.2941)
African American Proportion	2.7026***	2.6789***	2.7545***	2.7983***	1.0214
	(0.2054)	(0.1976)	(0.2084)	(0.2085)	(7.3746)
Asian Proportion	-2.3059***	-1.0699	-1.4635	-5.2742	-39.2056
	(0.8782)	(0.8435)	(0.9785)	(7.3964)	(34.3551)
Hawaiian/Native American Proportion	-2.6943***	-3.3678***	-3.3729***	-24.3757**	360.3545**
	(0.6475)	(0.7539)	(0.7537)	(11.1032)	(171.9380)
Log (Population Size)	1.0725***	0.8908***	0.8982***	0.9179***	0.4948
	(0.1173)	(0.1411)	(0.1404)	(0.1408)	(1.3187)
Socioeconomic Controls					
Log (Median Household Income)	-0.0065	0.0565	0.0447	0.0861	-0.6208
	(0.2028)	(0.2097)	(0.2086)	(0.2070)	(0.4100)
Log (No. of People in Poverty)	0.4113	0.5277**	0.5226**	1.2873***	0.2753
	(0.2604)	(0.2615)	(0.2633)	(0.4305)	(2.4708)
[Log (No. of People in Poverty)]^2	-0.0222**	-0.0254**	-0.0254**	-0.0265**	-0.0445
	(0.0113)	(0.0112)	(0.0113)	(0.0116)	(0.0990)
Log (No. of Home Mortgage Loans)	-0.0008	-0.0012	0.0075**	0.0080**	0.0038
	(0.0020)	(0.0020)	(0.0038)	(0.0038)	(0.0047)
Medical-Related Controls					
Prop. under Medicaid Coverage	0.2556***	0.2616**	0.2633***	0.2780***	0.3163
	(0.0991)	(0.1024)	(0.1020)	(0.1003)	(0.1952)
[Prop. under Medicaid Coverage]^2	-0.0016***	-0.0017***	-0.0017***	-0.0018***	-0.0019
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0012)
Prop. under Medicare Coverage	-6.7188	-10.7176*	-11.2453**	-10.4561*	5.7062
	(5.5206)	(5.6020)	(5.5053)	(5.4941)	(17.7227)
[Prop. under Medicare Coverage]^2	6.7505	8.1572	8.6976	7.7718	45.6173
	(7.7568)	(7.8739)	(7.8071)	(7.5549)	(36.7589)
Medicaid Coverage × Medicare Coverage	0.0343	0.0714	0.0764	0.0745	-0.1818
	(0.0580)	(0.0573)	(0.0559)	(0.0563)	(0.2227)
Log (Medicare Enrollees with Primary Care Visit)	0.7682***	0.7238***	0.5914**	0.4961*	-0.1093
	(0.2674)	(0.2682)	(0.2913)	(0.2919)	(1.0877)
Controls for type of healthcare utilization		✓	✓	✓	✓
Interaction terms with no. of fundraisers			✓	✓	✓
Interaction terms with poverty				✓	✓
No. of Observations	3770	3756	3756	3756	1363
Log Pseudo-Likelihood	2521.0773	2452.4445	2447.9465	2436.2889	

Table 3. Robustness Checks and IV Model (Continued)

	Random Coefficient Model				IV Regression
	(1)	(2)	(3)	(4)	(5)
R-squared					0.4144
Anderson-Rubin Wald test					18.25
Cragg-Donald Wald F statistics					14.655
Stock-Yogo critical values					9.08
Hansen J-Statistics					2.653

Note: In Model 2, on top of the core set of covariates, we added finer breakdowns of Medicare-related controls, which include the log cost of Medicare programs, log cost of hospice services, log number of users using hospital in-patient services, log number of emergency visits, and proportion of beneficiaries using skilled nursing facilities. In Model 3, we include interaction terms of fundraisers with the important demographic and health-related controls (i.e., age, race, mortgage loans, primary care visits, and emergency visits). In Model 4, we include interacted demographic factors (racial, age breakdowns) with poverty and include these as additional controls. In Model 5, we rely on three instrumental variables, namely the solicitation amount from coached campaigns, second lag of fraction raised, and the number of campaigns as a proportion to all campaigns posted in the same period. The Hansen J-Statistics in this over-identified model indicates that these excluded instruments are appropriately independent of the error process. Furthermore, C-Statistics of each of the instruments are 0.211, 0.045, and 2.651, respectively, indicating that exogeneity of these instruments is supported by the data. The Anderson-Rubin Wald test and Cragg-Donald F statistics suggest that this set of instruments are fairly strong instruments. A comparison of the Log (Amount Raised) estimates in Models 5 and 6 reveal that they are not statistically different from each other at conventional levels. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

We next consider the results of our IV regressions, which utilize three instruments, namely the amount solicited from coached campaigns, fraction raised in the previous period, and the proportion of all active campaigns in the United States attributable to the focal county. We report the results of the IV regression in Model 5 of Table 3. To assess instrument strength, we consider the *Anderson-Rubin Wald F test* and the *Cragg-Donald F*-statistic. Both tests are statistically significant at the 1% level, and the latter surpasses all of the critical values proposed by Stock et al. (2002). Based on these diagnostics, the set of instruments appears to be strong.[31]

With an over-identified specification, we can also test the over-identifying restriction, where the null hypothesis is that the set of instruments is uncorrelated with the error term. The Hansen J-Statistics from this specification is not significant at the conventional 5% level, indicating no evidence that our instruments are significantly correlated with the error. We further conduct a series of C-tests of individual instrument orthogonality. This test enables us to evaluate the exogeneity for each instrument, conditional on the assumption that all other instruments are exogenous. We observe C-statistics of 0.211, 0.045, and 2.651, each of which is statistically insignificant, again indicating no evidence that the proposed instruments are endogenous. Under this set of instruments, we find that the coefficient estimates for our key variable of interest remains negative and significant.[32] With the result from the instrumental variable analysis, we see that the negative effect of *Log(Amount Raised)* on bankruptcy remains robust after controlling for potential endogeneity.

Finally, in Table 4, we repeat our estimation employing the normalized measure of crowdfunding success, *Fraction Raised* (i.e., the ratio of funds raised to the total amount solicited in a county-quarter). The coefficient of *Fraction Raised* is negative and significant for the random coefficients models (Models 1 and 2). The estimate suggests that a one-unit increase in *Fraction Raised* (e.g., a shift from 0% to 100% of target) produces a 0.34% reduction in bankruptcy filings in a county-quarter, on average. Coefficients in the fixed effects specification (Models 3 and 4), although imprecisely measured, are negative, consistent once again with a bankruptcy dampening effect of medical crowdfunding.[33]

[31] The amount solicited from coached campaigns holds a positive relationship with amount raised, the while lagged fraction raised and the proportion of campaigns in a county hold negative estimates. Details of the first stage regression are available upon request.

[32] We note that, although the magnitude of the IV estimate is larger than those in the random coefficients model (i.e., Model 5 of Table 3), a Z-test of the equality of the IV and random coefficient estimates, based on the procedure presented by Cohen et al. (2003), is not statistically significant. This implies that we should prefer the random coefficient estimates, as they are likely to be more efficient and thus precise.

[33] This is expected, given that the Fraction Raised variable is noisier compared to the absolute measure of crowdfunding dollars raised. Fixed effect estimates are significant at the alpha = 0.15 level.

Table 4. Alternative Crowdfunding Activities: Fraction Raised

	Random Coefficient		Fixed Effect	
	(1)	(2)	(3)	(4)
Fraction Raised $_{t-1}$	-0.0337*	-0.0337*	-0.0317	-0.0317
	(0.0199)	(0.0204)	(0.0217)	(0.0215)
Demographic Controls				
Ages 25 to 64 Proportion	4.5020***	4.5020***	5.5818**	5.5818*
	(0.9272)	(1.0759)	(2.3267)	(2.9236)
Ages 65 and Above Proportion	-0.6229	-0.6229	2.9472	2.9472
	(0.9553)	(0.9353)	(3.9132)	(4.7625)
African American Proportion	2.7717***	2.7717***	3.9351	3.9351
	(0.2332)	(0.2112)	(2.8502)	(3.1659)
Asian Proportion	-1.4194	-1.4194	8.0636*	8.0636*
	(0.9224)	(0.9774)	(4.8518)	(4.7852)
Hawaiian/Native American Proportion	-3.3694***	-3.3694***	-9.4515	-9.4515
	(0.5884)	(0.7499)	(9.1017)	(7.6223)
Log (Population Size)	0.9097***	0.9097***	1.6193**	1.6193*
	(0.1387)	(0.1426)	(0.6884)	(0.8352)
Socioeconomic Controls				
Log (Median Household Income)	0.0208	0.0208	-0.3761	-0.3761
	(0.1944)	(0.2116)	(0.2771)	(0.3817)
Log (No. of People in Poverty)	0.5557**	0.5557**	-0.8285	-0.8285
	(0.2496)	(0.2651)	(0.9936)	(1.5260)
[Log (No. of People in Poverty)]^2	-0.0268**	-0.0268**	0.0415	0.0415
	(0.0113)	(0.0114)	(0.0481)	(0.0707)
Log (No. of Home Mortgage Loans)	0.0074	0.0074*	0.0077	0.0077*
	(0.0046)	(0.0039)	(0.0048)	(0.0046)
Medical-Related Controls				
Prop. under Medicaid Coverage	0.2735***	0.2735***	0.1908	0.1908
	(0.0976)	(0.1019)	(0.1546)	(0.1817)
[Prop. under Medicaid Coverage]^2	-0.0018***	-0.0018***	-0.0012	-0.0012
	(0.0006)	(0.0006)	(0.0009)	(0.0011)
Prop. under Medicare Coverage	-11.0822*	-11.0822**	-8.7467	-8.7467
	(5.9124)	(5.6433)	(8.2386)	(8.4789)
[Prop. under Medicare Coverage]^2	8.3119	8.3119	7.6282	7.6282
	(8.3049)	(7.7613)	(13.9942)	(15.1886)
Medicaid Coverage × Medicare Coverage	0.0789	0.0789	0.0726	0.0726
	(0.0613)	(0.0589)	(0.0811)	(0.0833)
Log (Medicare Enrollees with Primary Care Visit)	0.6475***	0.6475**	0.4666	0.4666
	(0.2382)	(0.2732)	(0.4726)	(0.7420)
Number of Observations	3683	3683	3683	3683
Clustered standard errors		✓		✓
F-statistics			29.9283	40.5771
R-squared			0.3141	0.3141

Notes: The dependent variable is the logged count of Chapter 13 bankruptcies. The main regressor, Fraction Raised, is lagged by one quarter. The set of covariates used are similar to that in Model 3 of Table 3. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Falsification Tests and Survey Results

We now report results from a series of falsification tests, as well as findings from primary data drawn from a survey of campaign organizers on GiveForward. First, we substitute business bankruptcy filings in place of personal bankruptcy filings, as a falsification check, to assess whether the statistically significant relationship identified thus far arise spuriously. We perform this test across the random coefficient, fixed effects, and negative binomial models. The results presented in Models 1–3 of Table 5 show that the *Log(Amount Raised)* variable does not hold a statistically significant relationship with business bankruptcy filings. The lack of significance across these estimations provides additional confidence that the primary results of our main model are not driven by unobserved macro-economic trends, nor are they driven by variation in the volume of nonmedical bankruptcies.

Second, we performed a series of three permutation (shuffle) tests, described earlier. Each check is based on random reassignment of values observed in our key independent variables (fundraiser volumes and amount raised) across observations in our panel. With each of the three approaches, we randomly assigned values in our panel, estimated our main model, and recovered the standard errors and coefficient estimates. The process was repeated 100 times. Ultimately, we calculated the average parameter estimate and standard error that resulted, and we assessed statistical significance, expecting to observe a null result.

In Model 1 of Table 6, we find the estimate for *Log(Amount Raised)* is not statistically significant when we reassign fundraiser volumes and amount raised across our panel, without preserving location, timing, or sequence of the observations. This suggests that our findings are dependent in some way on the combination of timing and location of crowdfunding activity. In Model 2 of Table 6, we repeat the process, but this time we preserve the timing and sequence of observations (i.e., we randomly reassign panels across locations). Once again, we see that the average coefficient estimates are statistically insignificant, this time suggesting that the primary results reported earlier are specifically dependent upon the location of crowdfunding activity, and thus are unlikely to be driven by macro-economic conditions.

By randomly assigning our crowdfunding measures specifically to counties in which no fundraising was taking place, the average estimates we recover for our two variables of interest once again fail to yield statistical significance. This serves as additional evidence that the reduction in Chapter 13 bankruptcies associated with increases in fundraising is unlikely to be a result of spurious association; rather, the relationship is dependent upon crowdfunding activity taking place in a certain place, at a certain time.

Finally, we consider primary data in the form of a survey of GiveForward users. Invitations to a web-based survey were sent via e-mail to a random selection of recent campaign organizers, for campaigns completed between August and October of 2014, where at least $100 was raised. GiveForward personnel issued the survey invitation on our behalf, informing potential respondents that the survey was conducted as part of an academic study and that valid responses would be compensated with a $5 Amazon gift card. To encourage participation and truthful responses, we informed respondents in the invitation email that they would remain anonymous. In total, survey invitations were received and read by 738 individuals, amongst whom 161 chose to respond, resulting in a conversion rate of 21.8%. We eliminated 28 responses based on specific disqualification criteria (i.e., failure to consent, incomplete response, nonmedical campaigns).[34] This resulted in a final set of 133 valid responses.[35]

We observed the following trends in the responses. First, approximately 82% of respondents stated that they faced medical treatment costs in excess of $2,500. In light of Lusardi et al.'s (2011) finding that more than half of American households would be unable to absorb an unanticipated expense in excess of $2,000, this result provides evidence of the financial burden faced by the patients raising money on GiveForward. More importantly, this statistic provides face validity for our main results by showing that medical crowdfunding is indeed used by individuals who have been subjected to a nontrivial financial shock and thus are likely to bear some bankruptcy risk. Second, in terms of the fraction of medical treatment costs that beneficiaries were able to offset via crowdfunding, over 30% of respondents indicated that the funds they obtained helped to cover at least 40% of their medical bills.[36] In addition, about 30% of our respondents indicated having considered filing for bankruptcy to

[34]We used screening questions to identify and exclude GiveForward users who were using the site for nonmedical purposes (e.g., funeral costs, pet relief funds, etc.). Since our aim is to assess whether users of medical-related crowdfunding are experiencing significant fiscal pressures from medical bills and their likelihood of filing for bankruptcy, we do not consider respondents who used GiveForward for other purposes.

[35]A summary of the responses to the demographic, financial, and insurance-related questions are provided in Appendix C, along with the survey questions.

[36]We note here that the descriptive statistics differ quite a bit from those of our estimation sample, suggesting the possibility of some bias in the sample of respondents. This affirms our earlier argument for why a pure survey-based methodology is inadequate in our study setting.

Table 5. Falsification Checks Using Business Bankruptcies

	Business Chapter 13 Bankruptcies		
	Random Coefficient	Fixed Effects	Neg. Binomial
	(1)	(2)	(3)
Log (Amount Raised)$_{t-1}$	0.0008	0.0054	0.0053
	(0.0039)	(0.0050)	(0.0122)
Log(No. of Fundraisers)$_{t-1}$	-3.1201	1.8268	-1.9823
	(2.6023)	(3.1513)	(6.1709)
Number of Observations	3756	3756	3756
Log Pseudo-likelihood	4051.103		6671.190
F-statistics		3.5332	
R-squared		0.0418	

Notes: The dependent variable in Models 1 and 2 is the logged count of business Chapter 13 bankruptcy filings, and that for Model 3 is the count of business Chapter 13 bankruptcy filings. The set of covariates used are similar to that in Model 3 of Table 3. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Table 6. Falsification Using Randomization of Values

	Random Coefficient		
	(1)	(2)	(3)
Log (Amount Raised)$_{t-1}$	0.0014	-0.0004	0.00001
	(0.0046)	(0.0032)	(0.0050)
Log (No. of Fundraisers)$_{t-1}$	-0.0071	0.0023	-0.0001
	(0.0239)	(0.0195)	(0.0455)

Notes: The dependent variable is the logged count of Chapter 13 bankruptcies. Each model represents the regression coefficients derived from the random assignment of the amount raised and number of fundraisers that was performed for 100 times. In Model 1, we randomly assigned the focal variables among the counties under study, without considering the temporal order in which these values appear. In Model 2, the random assignment is the same as that of Model 1, but preserving the temporal order of amount raised and number of fundraisers during the assignment. In Model 3, we randomly assigned the ordered set of amount raised and number of fundraisers to bankruptcy counts of counties that did not have any GiveForward fundraisers during the study period. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

avoid their medical debt. Finally, 35% of respondents stated that the money raised from GiveForward was very useful in avoiding bankruptcy, and an additional 58% stated that the funds raised were at least a little to moderately helpful. These results speak directly to the baseline result we report in our study: crowdfunding on GiveForward enables individuals to avoid medical-related bankruptcy.

Assessing the Digital Divide

Based on the analyses thus far, we see evidence of medical crowdfunding alleviating bankruptcy. However, more nuanced consideration is required if we wish to understand which populations see greatest benefit. Accordingly, we next examine heterogeneity in use and fundraising success across subpopulations, based on income, education and race.

We conduct this analysis in two ways. To assess the relationship between socioeconomic and demographic variables with medical crowdfunding access (use), we regress the number of crowdfunding campaigns on dynamic features of a county, including racial proportions, household income and education attainment, controlling for population size, home mortgage loans, insurance coverage, and the frequency of primary care visits. Subsequently, we explore whether these demographic and socioeconomic indicators significantly associate with successful fundraising, conditional on campaign volumes; that is, we regress the amount raised on the same set of variables, as well as the number of fundraisers. County and year fixed effects are incorporated into these regressions. We report the result of these analyses in Table 7.

In Model 1, we see that as African Americans, Asians, and Hawaiian/Native Americans represent larger portions of a county's population, campaign volumes rise significantly, sug-

Table 7. Factors Affecting Crowdfunding Intensity and Outcome

	Log (No. of Fundraisers)		Log (Amount Raised)	
Dependent Variable:	**(1)**	**(2)**	**(3)**	**(4)**
African American Proportion	6.5508***	6.2251**	7.5811	9.3284
	(1.6261)	(3.0277)	(4.9221)	(8.2412)
Asian Proportion	33.9067***	26.6694***	-26.7900**	-34.9556**
	(4.2011)	(5.2341)	(12.4998)	(16.0186)
Hawaiian/Native American Proportion	4.8269*	5.1941	-24.8137**	-72.2641***
	(2.8778)	(6.7836)	(10.9403)	(20.3405)
Log (Median Household Income)	-0.9153***	-0.8731***	1.4529**	0.8740
	(0.1634)	(0.3134)	(0.6593)	(1.1739)
Log (Population Size)	-0.3502	-0.6314	2.6120**	1.3347
	(0.3064)	(0.6556)	(1.0542)	(2.0899)
Log (No. of Home Mortgage Loans)	-0.0054*	0.0002	0.0043	0.0024
	(0.0028)	(0.0034)	(0.0108)	(0.0132)
Prop. under Medicaid Coverage	-0.0251***	-0.0314**	-0.0627***	-0.1170***
	(0.0064)	(0.0125)	(0.0237)	(0.0444)
Prop. under Medicare Coverage	-4.1209***	-6.0753***	0.7029	1.4476
	(0.4023)	(0.9988)	(1.3919)	(2.9889)
Log (Medicare Enrollees with Primary Care Visit)	0.1765	0.6022	0.5563	0.3015
	(0.1301)	(0.6626)	(0.5171)	(2.1102)
Log (Population with College or Associate Degree)		-0.1885		1.6617*
		(0.2128)		(0.8599)
Log(No. of Fundraisers)			3.8185***	3.7940***
			(0.0652)	(0.0783)
Number of Observations	6653	3416	6653	3416
F-statistics	203.4330	146.9378	416.5231	370.7247
R-squared	0.4624	0.5640	0.6123	0.6690

Notes: The dependent variable for Models 1 and 2 is the logged count of fundraisers, while that for Models 3 and 4 is the logged dollar amount raised. The unit of analysis is county-year, and all models are fixed effects specifications. Clustered standard errors are reported in parenthesis. *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

gesting that these populations are systematically more likely to host medical crowdfunding campaigns than white Americans. We also observe that household income has a negative relationship with the number of fundraisers initiated, which has a straightforward interpretation: populations with greater income are less likely to face financial pressure sufficient enough to drive them to solicit monetary resources via medical crowdfunding. We also observe that greater frequency of home mortgage loans has a negative relationship with crowdfunding campaign volumes, which suggests that access to home equity might reduce the need to solicit financial resources via crowdfunding (i.e., the two financial resources are substitutes for each other) (Agrawal et al. 2014). When the proportion of college and associate degree attainment is included as a regressor in Model 2, we see that the results remain largely similar. The negative coefficient on this variable indicates that locations with higher education attainment have a lower average demand for medical crowdfunding, although the difference is not statistically significant. In sum, these regressions suggest that economically and socially disadvantaged populations are systematically more likely to access these services. As such, these results suggest no evidence of a digital divide in access or connectivity when it comes to crowdfunding offerings.

We turn to the next set of regressions that look at the success in fundraising, and how that success associates with different population segments and socioeconomic status. In Model 3, we see that as Asians and Hawaiian/Native Americans, in particular, comprise a larger proportion of a county's population, systematically lower amounts of money are raised, conditional on the number of fundraisers being executed. This finding indicates that, although there is no evidence of a digital divide in access, there is a presence of a digital divide in the returns to usage. That is, despite these minority populations being in greater need (based on the relatively larger number of medical crowdfunding campaigns being conducted), they benefit systematically less compared to white populations.[37]

The same model also reveals that household income has a positive coefficient with fundraising outcomes, indicating that well-to-do families are likely to derive greater benefits from medical crowdfunding. When the proportion of college and associate degree attainment is added to the specification in Model 4, we find that the positive significance on household income dissipates, while the newly added education variable becomes positively significant. This set of estimates underscores the nuanced relationship between income and crowdfunding success: it seems that it is not wealth that leads to greater crowdfunding success, but education level (which is highly correlated with income levels) that is ultimately driving the divide in benefits reaped. Thus, our results suggest that racial minorities and populations with lower education attainment seem to yield a significantly lesser benefit from medical crowdfunding.

Discussion and Conclusion

This study investigates the impact of medical crowdfunding on bankruptcy levels in the United States. We employ a multimethod approach that accounts for a variety of threats to the validity of our estimation. We leverage data from both proprietary and public sources to evaluate the relationship between crowdfunding activity and bankruptcy filing rates across counties. We employ a variety of model specifications, an IV approach, and falsification tests to rule out concerns of estimation bias, inconsistency, and endogeneity. In addition, we conduct a survey of campaign beneficiaries to further assess the face validity of our main results. Finally, we explore potential mechanisms of the observed relationship by exploring the heterogeneous effects of medical crowdfunding on bankruptcy reduction.

In general, we find a consistent result: crowdfunding for medical expenses brings about a reduction in personal bankruptcy filing rates. Based on our estimates, a 10% increase in amount of funds raised leads to a 0.04% reduction in Chapter 13 bankruptcy filings. The economic significance of this relationship can be contrasted with the impact of alternative policy measures that are used to insulate against the prevalence of medical bankruptcies, documented in the literature. Under a state-year level analysis, Gross and Notowidigdo (2011) found that a 10% increase in Medicaid eligibility led to a 8% reduction in personal bankruptcies between 1994 and 2004. Through the Oregon Health Insurance Experiment where health insurance coverage was randomly awarded through lottery in 2008, Finkelstein et al. (2012) found that while lottery winners owed lesser medical debt, they did not experience lower rates of personal bankruptcy, delinquency, liens, or debt-related judgments such as wage garnishments. Further, a study on the 2006 healthcare reform in Massachusetts reported that a 10% increase in the reform was associated with a 0.3% reduction in personal bankruptcy (Mazumder and Miller 2016). Thus, prior work documents the effects of insurance coverage on bankruptcy rates with varying magnitude, with the two most recent studies reporting either no effect or small effects. Such findings are expected given that sharply rising medical costs in recent years have weakened the ability of medical insurance to shield individuals from financial distress (Himmelstein et al. 2009).

As we contrast the magnitude of these effects with those we have observed from medical crowdfunding, we should note that the scope of financial resources and the patients involved in each context may not be directly comparable, with the former representing an intervention of a larger, more comprehensive nature. With this in mind, it appears reasonable that an increase in crowdfunding contributions would have a smaller effect on bankruptcy reduction compared to the same percentage increase in insurance coverage. While the economic impact of medical crowdfunding on bankruptcy reduction may be considered modest at first glance, it is nonetheless economically meaningful, particularly when we consider that the dampening effect of crowdfunding on bankruptcy is operating over and above existing insurance-based measures. Given that we are likely to see diminishing marginal returns to any additional efforts directed at increasing insurance coverage, medical crowdfunding represents a potential solution for alleviating financial distress, and for supplementing insurance-based mechanisms that are known to face resource limits. Moreover, it should be kept in mind that the magnitude of the observed effects reflects one crowdfunding site, which only began to gain prominence in 2010.[38] As the awareness and use of medical crowdfunding platforms continue to grow, we can expect the magnitude of the effect of the medical crowdfunding phenomenon across all fundraising sites to increase in absolute terms. As such, crowdfunding's benefits suggest that the phenomenon should be encouraged further, because its cumulative impact over time could prove to be substantial.

[37] Interestingly, we find no evidence of systematically lower fundraising success being associated with African American populations, although we would caution the reader not to read too much into the null result.

[38] There were fewer than 500 campaigns initiated on GiveForward in 2009, yet more than 1,800 campaigns in 2010.

Our analysis also reveals that GiveForward's impact on bankruptcy acts through a specific segment of the population. Given that medical crowdfunding is largely effective in alleviating the rate of Chapter 13 bankruptcies, and not Chapter 7 bankruptcies, we see that its effect is limited to individuals who have an income stream for the debt repayment over time. An understanding of the scope of crowdfunding's effect is important for policymaking, as it underscores the fact that medical crowdfunding is not a panacea capable of resolving the medical bankruptcy crisis faced by the U.S. population, although its impact on providing financial relief is positively affirmed by our analyses. Medical crowdfunding should be considered as a secondary tool to complement other bankruptcy reducing policies to aid individuals with severe medical debt. Additionally, the fact that the benefits of medical crowdfunding accrue primarily toward people of systematically higher socioeconomic status (i.e., individuals who fail the means test) complements our finding of a digital divide in the returns to use (which we discuss next), when one considers that individuals most likely to file for Chapter 7 bankruptcies are those who lack assets and income.

As noted above, our results indicate the presence of a digital divide. Despite posting more campaigns than white Americans, individuals of minority descent face a more difficult time raising funds, indicating that the benefits of medical crowdfunding systematically accrue to populations that already hold greater wealth and education. This finding brings to light sources of inefficiency that may hinder the expansion and growth of medical crowdfunding. A primary step to enhance the social value of medical crowdfunding going forward would thus be to assist these underprivileged populations in achieving greater fundraising success. While platform operators might intervene by planning coaching services for underprivileged populations (instead of allocating coaches in an *ad hoc* fashion), the effectiveness of this remedy could be limited by the resource constraints that platform owners face. Addressing the digital divide at scale may therefore be better addressed via government agencies and policy makers. Policies could be crafted with the goal of closing the division by equipping underprivileged populations with better written and oral communication skills (e.g., reading, writing, and fluency in the use of technological devices and web-based software applications), to enable meaningful engagement with these digital platforms, such that all individuals can reap benefits, on a level playing field. Additionally, the platform might make a concerted effort to attract a greater volume of potential donors from minority groups, cognizant of individuals common preference for homophilous transaction partners (James 2000).

Noting that medical crowdfunding is utilized both by individuals who face severe bankruptcy risks and those who do not, an issue that requires deeper deliberation is whether access to monetary resources from crowdfunding sites should be prioritized based on financial distress. At present, beneficiaries who are most at risk of bankruptcy have to compete with those at lesser risk. It would also be prudent for platform owners to evaluate the basis of user's financial requests, especially for campaigns with extremely high monetary targets, such that there is less room for campaign owners to overstate their financial needs. The exaggeration of financial distress faced by beneficiaries can lead to an inefficient allocation of donations across campaigns. Beyond the issues of enhancing the efficacy of crowdfunding in alleviating bankruptcy, it is also valuable to consider the broader consequences of the phenomenon. For example, it is possible that the availability of this alternative funding mechanism as an ostensible source of "free" money may actually decrease patients' desire to seek out health insurance. Thus, it would be fruitful for future work to consider the relationship between crowdfunding and individuals' medical treatment and insurance decisions.

This work is not without limitations. First, our work found a relatively modest effect of medical crowdfunding on bankruptcy, which limits the practical significance of the phenomenon. Despite the small effect of medical crowdfunding, we are optimistic about the potential of this novel financial tool, given its growth trajectory. Moreover, our work has managed to trace the source of its inefficiencies to the digital divide. An understanding of the underlying reason to its modest effect provides actionable opportunities for stakeholders to improve its operation and delivery, and ultimately to increase successful utilization. Second, we do not have a clean measure of crowdfunding success; the closest proxy, *Fraction Raised*, based on the amount solicited, is a noisy approximation. This is because beneficiaries can easily overstate (or understate) their financial needs. As medical crowdfunding continues to improve and tighten its operations, future work might wish to revisit the relationships we study here, employing better measures of crowdfunding success. Finally, our findings are based on one crowdfunding platform. While our empirical strategy (via an IV approach) can tease out the unique contribution of GiveForward's impact on personal bankruptcies, we are unable to generalize our findings to other crowdfunding sites or the market more broadly.

In conclusion, we have found that medical crowdfunding has a significant, negative impact on the incidence of personal bankruptcy filing. Our results further indicate that the impact on bankruptcy is independent of alternative fundraising avenues or other economic trends. However, our results also suggest that medical crowdfunding's benefits do not accrue equally to all parties. Our findings thus have broad implications for the literature on IT in healthcare, the literature pertaining to treatment costs, societal implications of online platforms, as well as the literature on crowdfunding. Despite the evidence that online medical crowdfunding can improve patients' ability to locate and aggregate financial resources from the online social network, leading to a reduction in bankruptcy incidence, a result notably consistent with much of the recent crowdfunding literature (Agrawal et al. 2015; Lin et al. 2013; Mollick 2014), the presence of a digital divide limits the overall social benefits. It is our hope that this study can form the basis for future work in this area, given the apparent potential of crowdfunding to help relieve unmet healthcare costs and to reduce the burden of bankruptcy on individual patients and healthcare providers alike.

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RESEARCH ARTICLE

INVESTIGATING THE RELATIONSHIP BETWEEN MEDICAL CROWDFUNDING AND PERSONAL BANKRUPTCY IN THE UNITED STATES: EVIDENCE OF A DIGITAL DIVIDE

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Appendix A

Exponential Growth of Medical Crowdfunding

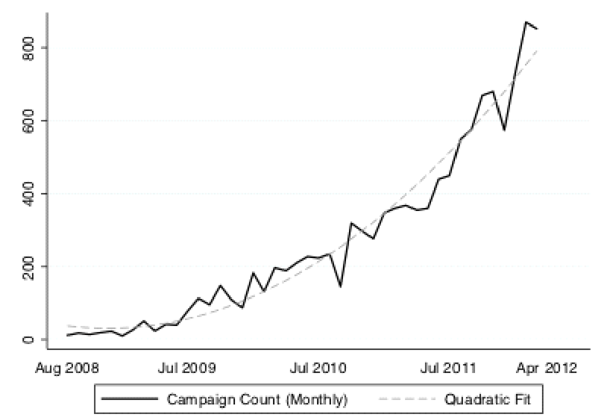

Figure A1. GiveForward Caompaign Volumes Over Time (Monthly)

Appendix B

Distribution of Target Fundraising Amount

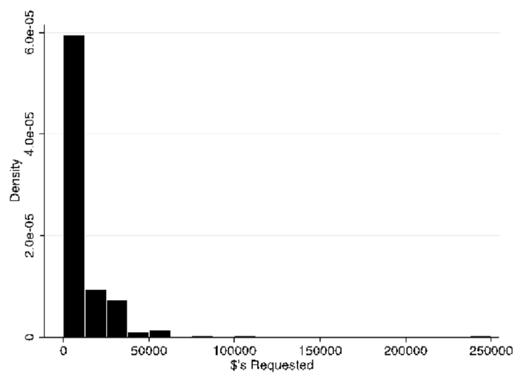

Figure B1. Histogram of Dollars Requested for Breast Cancer Campaigns

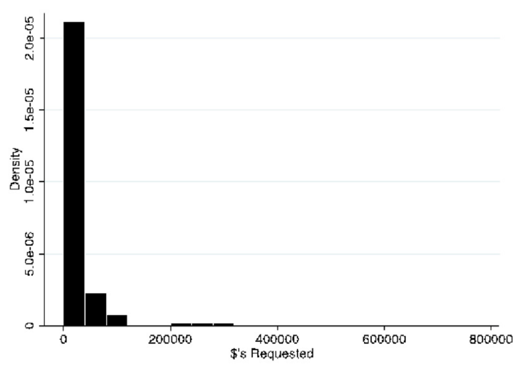

Figure B2. Histogram of Dollars Requested for Organ Transplant Campaign

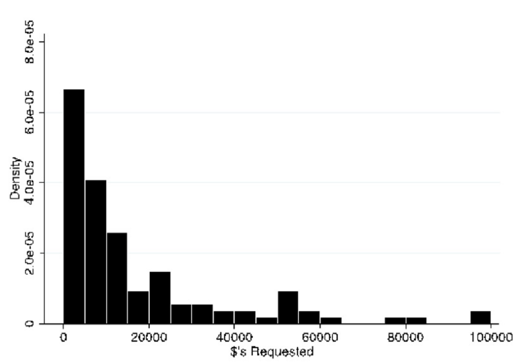

Figure B3. Histogram of Dollars Requested for Stroke Campaigns

Appendix C

Survey Items

Please select the **most accurate** response to each of the following questions:

1. You raised funds at GiveForward to
   - Support medical treatment costs for a chronic condition
   - Support medical treatment costs for a one-time procedure (e.g., a single surgery)
   - Support medical treatment costs for an accident-related injury
   - Compensate for a loss in income due to a medical event (e.g., to cover monthly bills)
   - Support a group medical cause
   - Other (please specify): ____

2. Who is/was financially responsible for the treatment costs (hereafter referred to as *financially responsible party*)?
   - Beneficiary
   - Legal guardian
   - Friend
   - Other (please specify): ____

3. What is the estimated total medical expense needed? ____

4. What proportion of the beneficiary's overall medical expenses was covered by the funds raised on GiveForward? ___________(0-100%)

5. What was the average **monthly disposable income** of the financially responsible party at the time of the fundraiser on GiveForward (i.e., after-tax income that is available following payment of regular bills and utilities)?
   - < $1,000
   - $1,000 to $1,999
   - $2,000 to $4,999
   - $5,000 to $9,999
   - $10,000 to $14,999
   - $15,000 to $25,000
   - > $25,000
   - Don't know.

6. Did the beneficiary's insurance provider cover the costs of the medical treatment?
   - No, he or she is not insured.
   - No, he or she is insured but the insurance does not cover this particular treatment.
   - Yes, his or her insurance provider covered all or a portion of the treatment cost.
   - Don't know.

7. What type of medical insurance does the beneficiary hold?
   - Public insurance (Medicare, Medicaid, Veteran, etc.)
   - Private insurance

8. To what degree were the funds raised helpful in avoiding personal bankruptcy on the part of the financially responsible party?
   - Not useful at all
   - A little useful
   - Moderately useful
   - Very useful

9. To what degree has the financially responsible party considered the possibility of filing for personal bankruptcy due to financial burden of the beneficiary's medical expenses?
   - Not at all
   - Thought about it, but not seriously
   - Thought about it moderately
   - Thought about it seriously
   - Don't know

Summary of Survey Responses

Variable	Proportion (%)	Cumulative Proportion (%)
Gender of Beneficiary		
Male	51.13	51.13
Female	48.87	100.00
Age of Beneficiary		
Younger than 10	18.05	18.05
10 to 19	4.51	22.56
20 to 29	13.53	36.09
30 to 39	24.81	60.90
40 to 60	30.08	90.98
Older than 60	9.02	100.00
Monthly Disposable Income		
Less than $1000	47.37	47.37
$1000 to $2000	17.29	64.66
$2000 to $5000	10.53	75.19
$5000 to $10000	0	75.19
$10000 to $15000	0.75	75.94
$15000 to $25000	2.26	78.20
Greater than $25000	21.8	100.00
Is Medical Cost Covered by Insurance?		
No, patient is uninsured	14.29	14.29
No, insurance does not cover expenses	18.05	32.33
Yes, insurance covers partial/full expenses	49.62	81.95
Other	7.52	89.47
Unsure	10.53	100.00
Type of Insurance (For Respondents with Insurance Coverage		
Public (Medicaid or Medicare)	27.27	27.27
Private	72.73	100.00