

Reducing Medical Bankruptcy Through Crowdfunding: Evidence from GiveForward

Completed Research Paper

Gordon Burtch

Carlson School of Management
University of Minnesota
gburtch@umn.edu

Jason Chan

Carlson School of Management
University of Minnesota
jchanf@umn.edu

Abstract

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. We consider the potential of online crowdfunding to alleviate the issue, wherein patients reach out to their social network for monetary support to help cover medical bills. We examine the effect of medical crowdfunding using proprietary data from one of the largest medical crowdfunding platforms, GiveForward.com, combined with state records of bankruptcy filing. Controlling for a variety of socioeconomic indicators, we find evidence that fundraising helped prevent between 114 and 136 bankruptcies across the US, per quarter, representing 3.9 percent of all medical related bankruptcies. Further, we explore the relationship between crowdfunding and public health insurance, finding evidence of a substitution effect when health insurance coverage is high. We discuss the implications of our findings for healthcare policy and crowdfunding.

Keywords: crowdfunding, bankruptcy, public health, medical insurance, policy

Introduction

It has been estimated that more than 50% of American households would be unable to absorb an unanticipated expense in excess of \$2,000 (Lusardi et al. 2011). It should therefore be unsurprising that a 2001 study reported that approximately 46% of individual bankruptcy filings in the United States were a direct result of costs borne due to illness or injury (Himmelstein et al. 2005), and that the proportion had grown to as high as 62% by 2007 (Himmelstein et al. 2009). When one considers that unmet healthcare costs are associated with more than 40,000 deaths and over \$30 billion in fiscal losses for health providers in the United States each year, the issue is troubling and obviously in need of some relief.

Here, we consider an increasingly prevalent practice that many patients are now undertaking to address the problem, namely online crowdfunding of medical expenses (Sisler 2012). Crowdfunding has been defined as “a collective effort by people who network and pool their money together, usually via the Internet, in order to invest in and support efforts initiated by other people or organizations” (Ordanini et al. 2010). Although entrepreneurs have attracted much of the media’s focus thus far when it comes to crowdfunding, a few studies and reports in the media have also highlighted its potential application to other areas of society where funding is often in question, such as journalism (Burtch et al. 2013b; Carvajal et al. 2012), scientific research (Gaggioli and Riva 2008; Wheat et al. 2013) and of course healthcare (e.g., Park 2012).

It is notable, however, that almost all of the reported benefits of crowdfunding in the healthcare space have been based on anecdotal or circumstantial evidence. Academic evaluations of crowdfunding to date have largely focused on fundraising by artists and entrepreneurs, with little research examining crowdfunding’s broader impacts on social outcomes. Indeed, other scholars have recently articulated a need for research into the effects of crowdfunding on societal welfare (Agarwal et al. 2013).

Assessments of crowdfunding’s impact on society are necessary in order to formulate appropriate, actionable public policies that can effectively assuage prevailing social and economic issues. For instance, a related concept, microfinance, has long been touted as a solution to reducing poverty, yet recent research has found little evidence that this actually manifests in practice (Angelucci et al. 2013). The question in this context, then, is whether crowdfunding for medical expenses truly has an impact on alleviating patients’ financial needs and, if so, to what degree.

There are a variety of reasons why crowdfunding might fail to deliver tangible benefits. For example, it is possible that crowdfunding merely offers limited and temporary reprieve for the focal patients without actually eliminating their financial debts, doing little to reduce the incidence of bankruptcies within a geographic region. As such, the social benefit of crowdfunding in this regard is not a given. Additionally, the digital divide literature would suggest that those individuals who are most likely to use nascent, online technologies are those who are in a better financial position to begin with (i.e., individuals who are tech savvy, and better educated). Accordingly, our work aims to bring clarity to these issues, which have important implications for healthcare policy and government legislation around medical crowdfunding. An understanding of these issues is also a crucial input to the decision-making of industry players, such as financial institutions, insurance agencies and healthcare providers.

To shed light on the phenomenon, we leverage publicly available data on quarterly bankruptcy filings across the United States, over the period between 2006 and 2011. We combine these statistics with proprietary data on monetary contributions made via the largest healthcare crowdfunding platform in the world, GiveForward.com. To account for endogeneity and heterogeneity, we employ instrumental variables and a fixed effect framework in our estimations. We find evidence that crowdfunding via GiveForward helped to reduce up to six bankruptcy filings in any given state, per quarter, for every \$1,000 raised. This effect translates into between 114 and 136 fewer personal bankruptcies across the U.S., in any given quarter¹. As a whole, the crowdfunding effort from GiveForward alone is able to reduce 3.9 percent of all medical related bankruptcies in the country.

¹ It is important to bear in mind that crowdfunding proceeds need not offset the entirety of a patient’s medical debt in order to eliminate a bankruptcy. Rather, at the margin, the proceeds would simply need to reduce a patient’s debt to a sufficient degree that there is no longer a financial benefit to their filing for bankruptcy.

We further explore a set of secondary analyses to evaluate the economic relationship between crowdfunding and public health insurance. In particular, we examine the moderating role of Medicare and Medicaid coverage when it comes to crowdfunding's impact on bankruptcy levels. Here, we find empirical evidence indicating the presence of a substitution effect between crowdfunding and public health insurance coverage, particularly in those states that exhibit high levels of the latter.

Our work builds on a number of streams of literature, including that on the subject of crowdfunding and the societal impacts of said (Agarwal et al. 2013; Burtch et al. 2013b; Burtch et al. 2014b; Kim and Hann 2013), as well as that dealing broadly with the impact of IT on healthcare, in terms of the incidence of illness (Chan and Ghose 2013), as well as in terms of reducing treatment costs and improving healthcare outcomes (Agarwal et al. 2010; Fichman et al. 2011).

The remainder of this paper proceeds as follows. In the following section, we provide a review of the literatures on medical bankruptcy and crowdfunding. In Section 3, we describe the context of our study and our data while formulating econometric models to assess the impact of crowdfunding activity on bankruptcy trends. In Section 4, we present the results of our model estimations and perform various robustness checks via alternative modeling approaches, as well as secondary evaluations around the economic nature between crowdfunding and health insurance. In Section 5, we discuss the implications of our results. Section 6 concludes.

Literature Review

Medical Bankruptcy & Unmet Healthcare Costs

Rising healthcare costs are a growing issue in the United States, for a number of 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 that lack health insurance. Notably, a recent Gallup poll indicates that almost one fifth of the American population is presently uninsured², a staggering proportion when we consider that it has now been three years since the approval of the United States Affordable Care Act, which was specifically intended to increase the level of healthcare coverage in the United States (Landers 2012). Unfortunately, failure to seek treatment is now associated with more than 40,000 deaths in the United States each year (Wilper et al. 2009).

This issue is not just one of mortality, as 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 catastrophic 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. This is because patients who are unable to cover their medical bills often file for personal bankruptcy, assuming there is a clear financial benefit to doing so (Fay et al. 2002; Gross et al. 2012).

Unmet treatment costs in these scenarios drive large fiscal losses for healthcare providers each year. Unpaid medical bills accounted for approximately \$30 billion in losses for US healthcare providers in 2005 (Gruber 2008), a number that has likely grown in recent years with the increased prevalence of personal bankruptcy. A recent study indicates that, as of 2007, approximately 60% of all individual bankruptcy filings in the United States were a direct result of costs borne due to medical treatment (Himmelstein et al. 2009). Further, these numbers reflect close to a 50% increase over the proportion of medical bankruptcies recorded in 2001 (Himmelstein et al. 2005).

There are multiple types of bankruptcy that individuals may pursue when faced with fiscal pressure. Roughly 70% of personal bankruptcies in the United States are filed through Chapter 7, which allows for the discharge of all unsecured debt (e.g., credit cards, utility fees and medical bills). The remaining 30% are filed through Chapter 13, which involves debt restructuring and the formulation of a repayment plan (Livshits et al. 2007). For the purpose of this study, we focus on Chapter 7 bankruptcies, as these

² <http://www.gallup.com/poll/153053/Texas-Widens-Gap-States-Percentage-Uninsured.aspx>

declarations are the most common type of bankruptcies among individuals and they bear the greatest impact on healthcare providers and institutions.

It is useful here to consider the consumer bankruptcy decision and the scenarios under which bankruptcy will be most likely to arise. As previously noted, this takes place when personal bankruptcy offers the individual a net financial benefit (Fay et al. 2002). This in turn, depends on a number of factors, including individual liquidity, wealth, and 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. 2012). Individuals will opt to file for bankruptcy when their net financial position, conditional on bankruptcy filing, exceeds their position they will retain without bankruptcy filing³. Put simply, if an individual could locate a source of funds that could improve their financial position, such that they no longer experience a net financial benefit from bankruptcy filing, then their probability of filing would be reduced. Notably, such effects would most likely manifest amongst those individuals along the indifference curve, where even a few hundred dollars of additional wealth could eliminate the financial benefit of bankruptcy filing.

Although bankruptcy has the benefit of eliminating or reducing pressure from credit collection agencies and the like, it should be kept in mind that it also has its downsides. One's ability to obtain access to credit following a bankruptcy declaration is severely reduced. There are also social costs to bankruptcy filing, as often individuals may experience social anxiety or shame. Further, bankruptcy is not a panacea, as there are many forms of debt that cannot be shirked in this manner. Further still, as noted above, though bankruptcy may be a beneficial recourse for patients, it forces healthcare providers to absorb the outstanding costs. Thus, if an approach could be identified that allows patients to meet treatment costs while avoiding bankruptcy filings, such a solution could enhance social welfare and would likely be preferred.

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, ideas and ventures. There are a number of variants of crowdfunding. The primary differentiator between these is the nature of incentives offered to contributors. Typical forms of crowdfunding include reward-based, lending-based and equity-based models (Burtch et al. 2013a). Recently, however, crowdfunding has also been adapted to a variety of other purposes, most notably fundraising for medical expenses. Medical fundraising typically falls under the donation-based crowdfunding framework, in which no formal incentive is offered in exchange for monetary contributions. Examples of this include sites such as YouCaring, GiveForward and IndieGoGo.

Though the overall crowdfunding movement has been successful in raising funds, it is unclear whether the specific genre of medical crowdfunding is effective in generating sufficient donations to aid those who are facing bankruptcy situations. Compared to reward-based models, donation-based crowdfunding not only denies contributors of financial returns, it can also experience a crowding-out effect (Andreoni 1989), to which potential donors relocate funds towards private consumption activities as the utility of giving from one's own acts of charity (i.e., warm glow effect) becomes reduced in the presence of high contribution volume from others (Burtch et al. 2013b; Roberts 1984). Moreover, given that donations to individuals on crowdfunding sites cannot be used for tax-deduction purposes, the price of giving on these avenues is perceived to be relatively higher than that of donating to non-profit organizations (Rose-Ackerman 1996), which can further dampen the success of medical crowdfunding campaigns.

Existing theories on digital divide also challenge the potency of medical crowdfunding in alleviating bankruptcy. The digital divide does not necessarily exist in terms of online access (e.g., Agarwal et al. 2009; Loges and Jung 2001), but rather in the divergence in Internet usage across various socioeconomic groups (e.g., Hargittai and Hinnant 2008; Shah et al. 2001). Individuals with higher education and income levels are more likely to possess the prerequisite online experience and skills to utilize Internet in

³ In referring to 'wealth' we mean net financial position, which may in fact be negative in the presence of debt.

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 the social welfare they receive. For instance, Howard et al. (2001) found that online activities such as searching for financial, political, and government information and the use of online banking are all associated with higher education. Furthermore, users with more education and income are more likely to use the Internet for capital-enhancing purposes, which include seeking news, retrieving financial and health information, researching products, looking for jobs, and for work purposes (Boyce and Rainie 2002; Hargittai and Hinnant 2008; Madden 2003).

In line with the usage predictions of the digital divide, large crowdfunding platforms mainly receive participation from the highly educated population⁴. Thus, only a select group of individuals may actually tap on medical crowdfunding to finance their treatment and healthcare costs. Based on trends from past studies, the population that would most likely attempt to raise funds on medical crowdfunding sites consists of people who belong to the mid and high SES groups, as these individuals are savvy enough to utilize Internet technologies to their advantage (Mossberger et al. 2003). The positive impact of crowdfunding on reducing bankruptcy rates is therefore not apparent because the bankruptcy-prone populations may not be well connected to the fundraising affordances of this nascent online phenomenon. Instead, the bankruptcy-reducing benefits of medical crowdfunding efforts may accrue narrowly to the mid-level SES population group, especially for those whose existing finance sources are able to absorb a significant amount of medical-related expenses, leaving a small sum of open costs which may be covered by crowd-based donations.

The focal study contributes broadly to the emerging stream literature that examines the economics of crowdfunding platforms, including the works of Lin et al. (2013), Agarwal et al. (2011) and Ahlers et al. (2012), who respectively study lending-, reward- and equity-based crowdfunding platforms, by identifying and quantifying the influence of various factors on crowdfunders’ contributions toward various campaigns. Common amongst prior studies has been a near exclusive focus upon within-platform behavior and outcomes. That is, very little work has explored ‘off-platform’ effects from crowdfunding. The few examples that do exist, to our knowledge, include the following.

First, Mollick (2014) examines whether and how quickly entrepreneurs deliver the rewards they promise to contributors at Kickstarter. This work is motivated by the observation that crowdfunding platforms typically provide little guarantees or assurances of project implementation or product delivery. Second, Burtch et al. (2013b) study the association between contribution patterns in the crowdfunding process and the subsequent consumption (readership) of published journalism articles. The notion underlying that work is an effort to understand how contribution dynamics impact funding durations, and how funding durations, in turn, impact the ability of campaigns to build awareness and buzz in the marketplace. Third, Kim and Hann (2013) study the degree to which crowdfunding actually ‘democratizes’ access to capital for entrepreneurs, as has long been touted in the media. The authors explore variation in crowdfunding’s uptake by entrepreneurs with geographic variation in credit shortages.

Further, amongst the work on crowdfunding, little consideration has been given to its impact on society, a fact recently acknowledged by Agarwal et al. (2013). In particular, no prior work has considered crowdfunding’s application on alleviating medical debts. Our study therefore offers a step forward in this regard and attempts to do so by assessing the effect of medical crowdfunding on bankruptcy levels in the U.S.

Methods

Study Context & Data

With over 100,000 users since its inception, GiveForward.com is currently the largest medical crowdfunding website in the US. This platform has helped individuals to raise nearly \$100 million

⁴ For instance, Quantcast reports that 62% of the users at Kickstarter have either college or graduate school education: <https://www.quantcast.com/kickstarter.com/demographics>.

towards medical expenses⁵. Other causes supported by the platform include memorial and funeral costs, disaster relief and pet medical expenses. For the purpose of this study, we focus specifically on fundraisers for medical expenses to understand whether crowdfunding efforts catered towards medical expenses have an impact on alleviating bankruptcy trends.

To study the effect of crowdfunding on the rate of bankruptcy filing, we construct a novel panel dataset by combining publicly available data from the US court system, with proprietary data provided by the largest medical crowdfunding platform, GiveForward.com. The bankruptcy data is obtained from the Harvard Bankruptcy Data Project⁶. We obtain the total number of Chapter 7 individual-based bankruptcy filings, by state and year-quarter, between the first quarter of 2006 and the fourth quarter of 2011. We focus only on US states in which GiveForward beneficiaries reside.

Our main independent variable captures the amount of medical crowdfunding activity on GiveForward. For each fundraiser listed on the GiveForward site, we have data on the geographic location of the beneficiary, as well as the dollar amounts requested and raised. Based on this information, we construct a measure of medical crowdfunding activity, *AmountRaised_{it}*, which captures the aggregate funds raised in support of medical purposes in a particular state for a specific year-quarter. We note that the GiveForward website was launched in the third quarter of 2008, implying that the donation amounts raised in periods prior to 2008 Q3 are zero. By constructing a panel of donation activity that spans from 2006 to 2011, we are able to observe and contrast the changes in bankruptcy levels before and after the introduction of GiveForward to the US, allowing us to draw empirical conclusions that are based on observing bankruptcy outcomes in counterfactual scenarios. In constructing the variable of *AmountRaised_{it}*, we have specifically included only monetary amounts that are already paid out to beneficiaries from GiveForward. The use of donation amounts capture the activity level of the platform in various states at year-quarters, thereby providing information on the “treatment intensity” which can be meaningfully exploited in empirical models towards causal interpretations.

We combine the data on bankruptcy and crowdfunding activity with a set of demographic and socio-economic indicators. These indicators are included as covariates to account for time varying demographic and socio-economic trends that may influence the incidence of bankruptcy filings within each state over time. Bankruptcy rates have historically been found to have a strong association with a number of factors, most notably divorce rates, unemployment levels, and home ownership rates (Domowitz and Sartain 1999). Marriage allows individuals to obtain assistance from a spouse when facing financial distress, sharing the burden. Accordingly, divorce eliminates this possibility. In addition, divorce often comes with significant financial burdens associated with legal fees and asset reallocation. Next, unemployed individuals have no source of stable income to pay for living expenses and recurring bills. As such, unemployed individuals have a greater need to take on debt. Yet, unemployed individuals have poorer access to credit, which increases the likelihood of bankruptcy. Lastly, homeownership provides individuals with a source of equity on which they can draw in times of financial stress. It should be noted, however, that while Domowitz and Sartain (1999) report homeownership’s negative association with bankruptcy, Zhu (2013) reports a positive association, observing that a home purchase represents a large personal expenditure and the acquisition of a large debt. To control for these demographic and socioeconomic factors, we obtained data on divorce rates from the Center for Disease Control’s National Vital Statistics Report, unemployment rates from the Bureau of Labor Statistics, and homeownership rates from the US Census Bureau.

In addition to the covariates listed in extant literature, we further include other controls, which capture other factors that have the potential to affect bankruptcy trends. We collected state-level population sizes over our period of observation from the US Census Bureau. This measure is based on a combination of intercensal population estimates (available through 2010) and predictions (for 2011).⁷ On top of population size, we control for cost of living via the state-level prices of utilities and healthcare at each

⁵ Note: Give Forward makes explicit mention of how crowdfunding can aid patients in financial distress, helping them to avoid bankruptcy: <http://www.giveforward.com/p/medical-bankruptcy>

⁶ Data is retrieved from <http://bdp.law.harvard.edu/filingsdb.cfm> on Jan 15, 2013.

⁷ We rely on population predictions for the latter portion of our period of observation because state population had not been formally tabulated for the year 2011 at the time of this article’s writing.

year-quarter to account for varying economic conditions across locations and time. These price indices are taken from the Missouri Economic Research and Information Center, which calculates quarterly price information from the surveys conducted by Council of Community and Economic Research. Descriptive statistics for each of our study variables are provided below in Table 1.

Variable	Observations	Mean	Std. Deviation	Min	Max
No. of Bankruptcies	894	3326.65	3536.67	71	21610
Amount Raised (in 1000s)	894	6.19	19.79	0	335.85
Population Size (in 10,000s)	894	1248.13	1226.50	118.51	5727.98
Divorce Rate	894	3.76	0.88	1.7	6.7
Utility Costs	894	103.44	14.82	73.8	163.73
Healthcare Costs	894	102.17	11.67	71.4	211.8
Unemployment rate	894	6.75	2.51	2.4	14.13
Proportion of Home Ownership	894	69.42	5.68	43.3	80.8

Considering our descriptive statistics, it is interesting to note that the basic association between fundraising activities on GiveForward and the volume of bankruptcy filings across the United States. In Figure 1 below, we provide a time series plot comparing fundraising activities and bankruptcy filings. An immediate observation is that these two trends run contrary to one another – as fundraising activity on GiveForward begins to pick up in the second quarter of 2010, bankruptcy filings peak and begin to decline. In support of the trend on this figure, the statistical correlation between total bankruptcy filings and GiveForward fundraising activity is highly negative ($\rho = -0.36$). Although this does not provide conclusive evidence of a crowdfunding effect, it does provide initial support for the notion that bankruptcy filings and crowdfunding activity are likely to be inversely related.

Hypotheses & Econometric Specifications

Our analysis aims to assess the impact of fundraising at GiveForward.com on the level of bankruptcy filings in a particular state, i , for a particular quarter, t . Our outcome of interest is the aggregate number of Chapter 7 individual bankruptcy filings. Our review of the literature, above, and logical intuition would jointly suggest that increased access to financial resources would lower the probability of personal bankruptcy filing. Given that more than 60% of all personal bankruptcy filings in the United States are reportedly attributable to medical expenses, it stands to reason that increased success in crowdfunding for medical expenses, amongst patients in a particular state, would lead to a subsequent decline in the rate of bankruptcy filing in that same state. Accordingly, we propose the following hypothesis.

H1: Greater fundraising by patients in a particular state will result in fewer personal bankruptcy filings.

In testing this hypothesis, we must consider a number of alternative, perhaps confounded influences on bankruptcy filings. To account for potential omitted variables bias, we employed a lagged dependent variable (LDV) specification to capture effects from any unobserved factors that may affect the incidence of bankruptcies in the states at each year-quarter. LDV models have been shown to produce estimates with relatively low bias compared to other models (such as regressing Y_t on X_t), except in situations where there are high levels of autocorrelation in the error term (Keele and Kelly 2006). In practice, models with LDV often do not show evidence of autocorrelation. Moreover, the inclusion of LDV can have the effect of cleaning up existing serial correlation. The use of a LDV specification in our study is also guided by existing literature, wherein numerous studies note that bankruptcies induced by unfavorable macroeconomic conditions are likely to be dependent on their past levels as economic climate usually persists over several quarters. On top of the LDV approach, we also include a series of demographic, cost of living, and socioeconomic covariates described earlier, to control for the extraneous effects that may shift bankruptcy levels over time.

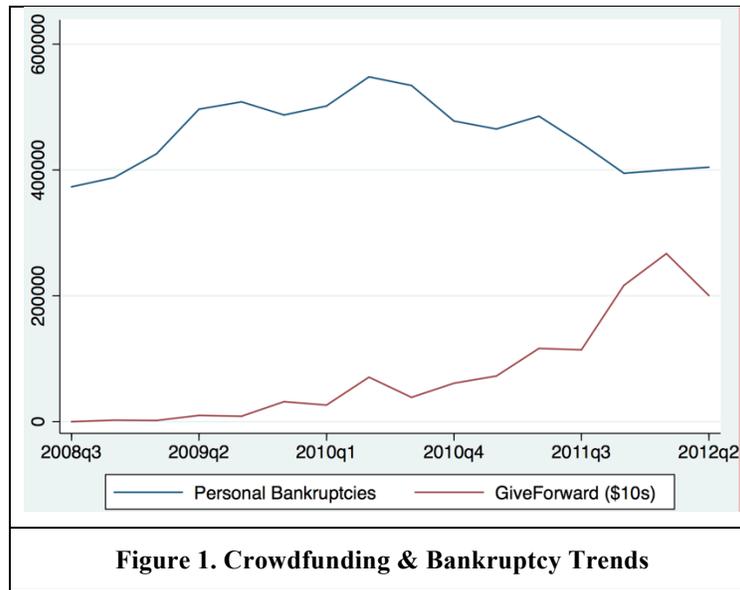


Figure 1. Crowdfunding & Bankruptcy Trends

Next, in accounting for unobserved heterogeneity across locations and time, we employ the use of fixed effects in our models. Significant differences in the prevalence of bankruptcy across state lines that are not explained by socioeconomic status or other such factors have been noted (Lefgren and McIntyre 2009). Accordingly, it has been suggested that these differences may be attributable to variation in the cultural acceptability of bankruptcy across geographic regions. Such cultural norms are effectively intangible, and are therefore difficult to control for directly. Additionally, exogenous temporal shocks such as the rollout of bankruptcy relevant policies and the variation in business cycles may introduce systematic shifts to bankruptcy levels over time. Indeed, it is well documented that credit card default and bankruptcy rates follow a highly cyclical pattern, being inversely correlated with the performance of the broader economy (Ausubel 1997). We therefore leverage state and time fixed effects to address unobservable heterogeneity across locations and year-quarters. Based on these empirical strategies, we present our primary estimation model below in Equation 1.

$$Bankruptcies_{it} = \beta_1 Bankruptcies_{i(t-1)} + \beta_2 AmountRaised_{it} + \alpha X_{it} + \delta_i + \gamma_t + \varepsilon_{it}. (1)$$

Here, states are indexed by i , and year-quarters are indexed by t . X_{it} is a vector of time-varying state-level covariates as noted above. The remaining terms, δ_i and γ_t , capture the state and time fixed effects, respectively. Our primary parameter of interest here is β_2 , the effect of fundraising dollars at GiveForward on the incidence of bankruptcy filing. A negative coefficient would be taken as evidence in support of our first hypothesis.

We evaluate the robustness and validity of our results in a number of ways. First, we consider the possibility that the contribution activity on GiveForward may be endogenous. For example, it may be that the donation amounts at GiveForward reflect the increase in the disposable wealth of individuals in a particular geography, which is in turn associated with lower rates of bankruptcy. If this were the case, coefficients on the $AmountRaised_{it}$ would simply capture the shifts in disposable income and wealth for a particular populace. Although we include lagged dependent variables and control for state economic conditions, such as unemployment rates and cost of living, it is still possible that our model does not capture certain relevant economic factors. In order to address potential endogeneity bias, we explore a plausibly exogenous instrumental variable (IV): the number of page views for GiveForward fundraisers from other states. Page views from fundraisers in other states is a valid instrument as it is likely to be correlated with donation and contribution levels on GiveForward, while at the same time it is unlikely to be correlated with general economic fluctuations and the disposable income of the local populace in the focal state. Similar IVs of this kind have been used in previous studies (Burtch et al. 2013b; Desiraju et al.

2004). To validate our assumptions on validity of the IV, we provide additional empirical checks in the results section.

Second, given that our outcome measure is the number of bankruptcy filings, which is a positive integer value, it could be argued that a count estimator is most appropriate. Accordingly, as an alternative check, we re-estimate our model using count data estimators. This allows us to assess whether the baseline coefficients are adversely affected by the use of non-linear model specifications. In these count data specifications, we employ both the conditional fixed effects Poisson estimator, as well as a negative binomial estimator incorporating dummy fixed effects (Allison and Waterman 2002).

Third, given that our study analyses are at the aggregate level, it may be argued that the individuals who are fundraising on the platform may not correspond to the same population that has filed for bankruptcy. As such, any effect that fundraising has on bankruptcy level may arise spuriously from omitted variables. To verify the validity of our results, we supplement our main results with an individual-level analysis, searching for the names of GiveForward campaign organizers within public court records for individual bankruptcy filings. In doing so, we exclude those identified cases where the bankruptcy filing took place prior to the launch of the associated fundraising campaign. We then paired “bankruptcy” campaigns with an equal number of “non-bankruptcy” campaigns (i.e., where no bankruptcy filing was located). We did this twice, first taking a simple random sample, and then constructing a matched sample based on campaign characteristics – namely in terms of the target fundraising amount.

We then compared the rate of fundraising success between the “bankruptcy” associated and “non-bankruptcy” associated fundraisers, to identify statistically significant mean differences in fundraising success. In particular, we performed a t-test to examine whether the percentage of the target amount raised in the “bankruptcy” fundraisers differed statistically from that in the “non-bankruptcy” fundraisers. The idea here is that, if the effect observed earlier were indeed spurious, we would not expect the fundraising success of “bankruptcy” campaigns to be significantly different than that of “non-bankruptcy” campaigns. In contrast, if the fundraising success of “bankruptcy” associated campaigns is lower than that of the “non-bankruptcy” associated campaigns, we have greater assurance that crowdfunding efforts on GiveForward do have a true dampening effect on bankruptcy levels.

Secondary Analyses

Following our primary analyses, we explore a set of additional analyses to understand the economic relationship between medical crowdfunding and other types of financial resources when it comes to reducing personal bankruptcy rates. To this end, we consider the interaction between crowdfunding outcomes and public health insurance. As evidenced in recent studies, the availability of public health insurance alleviates the financial burdens that arise from out-of-pocket medical costs (Finkelstein et al. 2012, Gross and Notowidigdo 2011). Though both public health insurance and medical crowdfunding serve similar purposes, dampening bankruptcy levels, it is unclear whether they are used independent of each other – i.e., as substitutes – or if they are utilized in conjunction, as complements. Given that we have no strong theoretical or empirical evidence in support of either relationship, we propose two competing hypotheses, H2a and H2b.

H2a (Complement): Greater public health insurance coverage in a particular state will magnify the effect of medical crowdfunding on personal bankruptcy filings.

H2b (Substitute): Greater public health insurance coverage in a particular state will attenuate the effect of medical crowdfunding on personal bankruptcy filings.

In examining this economic relationship, we consider the two prevailing sources of public health insurance, Medicare and Medicaid, both of which are made accessible to specific population groups. Medicare serves the population of elderly and disabled individuals, while Medicaid caters to low income populations of all ages. In contrast to public health insurances, there are no restrictions enforced on the type of patients that could solicit medical financing on medical crowdfunding platforms. An immediate implication is that medical crowdfunding may complement Medicare and Medicaid by catering towards individuals who are not already served by these two types of public insurance, resulting in a greater reduction in the number of bankruptcies. However, there may be intrinsic factors of medical

crowdfunding that may reverse this complementary relationship. For instance, the success in raising funds on medical crowdfunding may be restricted to beneficiaries that overlap with those covered by Medicare such as children and elderly, as donors are more likely to show compassion towards such individuals. Moreover, eligible individuals may choose not to enroll in Medicare or Medicaid to avoid paying monthly premiums. Under these possibilities, the overlap in population groups served by both medical crowdfunding and public health insurance can lead to a substitution effect between the two.

To understand the economic relationship between medical crowdfunding and public health insurance, we obtain data on Medicare and Medicaid coverage from the U.S. Census Bureau's Current Population Survey. This data shows the percentage of population covered by the two health insurance schemes in each state across all study years. To simplify the analysis, we add the two percentages to reflect the overall coverage provided by public health insurance. Based on this data, we create binary indicators to denote state-quarters that are above 1) the median coverage, 2) upper quartile coverage, and 3) top decile coverage. By empirically investigating the moderating effect of insurance coverage over different splits, we get to understand not only the nature of the relationship but also the extent of this relationship. In particular, we perform the following analysis.

$$\begin{aligned} \text{Bankruptcies}_{it} = & \beta_1 \text{Bankruptcies}_{i(t-1)} + \beta_2 \text{AmountRaised}_{it} + \beta_3 \text{Coverage}_{it} + \\ & \beta_4 \text{AmountRaised} \times \text{Coverage}_{it} + \alpha X_{it} + \delta_i + \gamma_t + \varepsilon_{it}. \end{aligned} \quad (2)$$

Under this specification, β_3 captures the main effect of increasing public health insurance coverage on bankruptcy filing rates. In addition, β_4 captures the interaction between medical crowdfunding and public health insurance coverage. If medical crowdfunding and public health insurance play a complementary role in reducing bankruptcies (H2a), we would expect the coefficients for the main and interaction effect to lie in the same direction, i.e., $\beta_4 < 0$, such that the interaction term indicates that the combined effect of health insurance and crowdfunding creates a stronger reduction in bankruptcies. On the other hand, if medical crowdfunding and public health insurance are substitutable in nature (H2b), we would expect the coefficient on the interaction term to hold the opposite sign from the main effect, i.e., $\beta_4 > 0$, such that increases in insurance coverage mitigate the impact of crowdfunding on bankruptcy rates.

Results

Main Result

We report the results of our LDV-fixed effects analysis in Table 2. In this table, we include the control variables in a hierarchical fashion to understand whether the coefficient on *Amount Raised*_{it} is sensitive to the effects from the covariates. Two immediate observations can be made. First, the lagged dependent variable is positive and significant across all models, supporting our earlier claim that bankruptcy trends are highly dependent on past bankruptcy levels. This observation motivates for the use of a LDV specification to control for estimation biases. Second, we observe that the coefficients for *Amount Raised*_{it} are negative and significant after controlling for location and time heterogeneity, and remain relatively stable with the inclusion of various bankruptcy-related controls. Based on the results in the regression models with state and time fixed effects, we find that a \$1000 raised on GiveForward is related to a decrease in approximately four bankruptcies in a state over a year-quarter.

Instrumental Variable Result

To account for potential endogeneity of the contribution activity, we next run an IV regression using the number of fundraiser page views from other states as an instrument for *Amount Raised*_{it}. We report the results of the IV regressions in Table 3. To assess instrument strength, we turn to the Kleibergen-Paap F-statistics and contrast them with the critical thresholds for weak instruments. These F-statistics are significant at the 1% level and surpass the critical values given by Stock and Yogo (2005).

Based on the diagnostic, the number of page views satisfies the correlation requirement for IVs and is unlikely to suffer from weak instrument biases. In the second stage regressions, we find that the coefficients for our key variable of interest, *Amount Raised*, are negative and significant for all models. In

particular, the estimates suggest that \$1000 raised via GiveForward is linked with five to six fewer bankruptcies. Based on the estimate size, it seems likely that the amount raised is used to alleviate individual debts that are on the fringe of bankruptcy filing, instead of offsetting the entirety of a patient’s medical debt.⁸

Table 2. LDV-Fixed Effect Regression				
DV: No. of Bankruptcies	(1)	(2)	(3)	(4)
No. of Bankruptcies $t-1$	0.864*** (0.03)	0.858*** (0.03)	0.857*** (0.03)	0.832*** (0.03)
Amount Raised (in 1000s)	-3.580*** (0.66)	-3.892*** (0.55)	-3.861*** (0.54)	-3.896*** (0.53)
Demographic factors		✓	✓	✓
Cost of living metrics			✓	✓
Socioeconomic factors				✓
Time dummies	✓	✓	✓	✓
R-squared	0.928	0.928	0.928	0.930
F statistics	1976.486	1706.806	2446.471	1060.324
Observations	894	894	894	894

Notes. Dependent variable is count of bankruptcies for each state in a year-quarter. Robust standard errors in parentheses. Time dummies based on year-quarter. Demographic factors include population size, divorce rate, cost of utilities and healthcare services. Socioeconomic factors include unemployment rate and proportion of home ownership. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Robustness Checks

To assess the robustness of the main results, we first consider a set of count data model specifications and estimators. In particular, we re-estimate our model using a fixed effects Poisson model and a fixed effects negative binomial model. By considering the latter count data model in our check, we are effectively accounting for over-dispersion in the bankruptcy variable. These results are presented below in Table 4. We see results that are qualitatively similar to those in previous specifications, i.e., $AmountRaised_{it}$ hold negative and significant coefficients across both count data models. Given that the level of bankruptcies exhibit overdispersion (see Table 1), the negative binomial model appears to be a more appropriate specification for fitting the data.

Empirically, we also observe a significant estimate for the dispersion parameter in our negative binomial estimation, providing direct evidence of its increased efficiency over the Poisson estimation. Converting the coefficient estimate for $AmountRaised_{it}$ from the negative binomial model into more concrete terms, we observe that each additional \$1,000 raised on GiveForward translates to approximately 11 fewer bankruptcies, at the average.

Next, we check the validity of the results by comparing the fundraisers whose owners have filed for bankruptcy (i.e., campaigns matched to public individual bankruptcy records) with those that have not filed for bankruptcy (i.e., unmatched campaigns). The comparison is done in two ways. The first method involves picking an equal number of campaigns randomly from the non-bankrupt pool for comparison.

⁸ Our interpretation here is that \$1000 raised over a state-quarter helps five individuals on the margin of bankruptcy to avoid filing (i.e., people who have other sources of financial help and savings); rather than that \$1000 helps five completely insolvent individuals to pay off the entirety of their medical debts.

Table 3. 2SLS-Fixed Effect Regression				
DV: No. of Bankruptcies	(1)	(2)	(3)	(4)
No. of Bankruptcies _{t-1}	0.870*** (0.02)	0.862*** (0.02)	0.860*** (0.02)	0.836*** (0.02)
Amount Raised (in 1000s)	-5.171** (2.10)	-5.883** (2.45)	-5.806** (2.45)	-5.634** (2.42)
Demographic Factors		✓	✓	✓
Cost of living metrics			✓	✓
Socioeconomic factors				✓
Time dummies	✓	✓	✓	✓
Kleibergen-Paap F statistic	26.562	20.707	20.649	20.886
Kleibergen-Paap LM statistic	9.258	9.515	9.574	9.573
R-squared	0.928	0.928	0.928	0.930
F statistics	439.76	413.81	382.24	348.12
Observations	894	895	896	897

Notes. Models 1 to 4 are 2SLS regressions with state level fixed effects. Robust standard errors are reported in parentheses. Time dummies are at the year-quarter level. Demographic factors include population size, divorce rate; cost of living metrics include the utility cost and healthcare cost; socioeconomic factors include unemployment rate and proportion of home ownership. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4. Count Regressions		
DV: No. of Bankruptcies	FE Poisson (1)	FE Neg. Binomial (2)
No. of Bankruptcies _{t-1}	3.01E-5*** (6.75E-6)	3.57E-5*** (6.11E-6)
Amount Raised (in \$1000s)	-0.001** (0.0004)	-0.002*** (0.0004)
Demographic factors	✓	✓
Cost of living metrics	✓	✓
Socioeconomic factors	✓	✓
Log likelihood	-29687.24	-6398.84
Observations	894	894

Notes. All models are count data models, with includes fixed effects. Robust standard errors are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

	Random Sample	Matched Sample
Non-Bankruptcy % Raised	0.172 (0.042)	0.189 (0.052)
Bankruptcy % Raised	0.089 (0.025)	0.089 (0.025)
<i>t</i> -Test	0.083** (0.049)	0.100** (0.058)

Notes. Values in each cell represent the means and standard deviation of the percentage of target amount raised for each group. We report one-tailed t-test of differences in the % of target raised between non-bankruptcy and bankruptcy campaigns.

	Fixed Effects Regression			Control Function Regression with Fixed Effects		
	Median	Upper Quartile	Top Decile	Median	Upper Quartile	Top Decile
DV: No. of Bankruptcies	(1)	(2)	(3)	(4)	(5)	(6)
No. of Bankruptcies t_{-1}	0.830*** (0.03)	0.832*** (0.03)	0.834*** (0.03)	0.833*** (0.03)	0.836*** (0.03)	0.838*** (0.03)
Amount Raised (in 1000s)	-3.048** (1.19)	-4.772*** (1.30)	-4.772*** (0.74)	-5.252*** (1.29)	-6.030*** (1.14)	-6.349*** (0.90)
Percentage of Insurance coverage	52.199 (55.69)	-51.723 (59.16)	-24.111 (59.03)	57.032 (55.04)	-54.490 (57.63)	-29.523 (60.23)
Amt Raised x Coverage	-0.946 (1.11)	1.193 (1.25)	4.212*** (0.68)	-0.426 (1.06)	0.635 (1.65)	3.999*** (0.71)
Control Function Residuals				4.116** (1.84)	3.927* (2.08)	3.837** (1.80)
Demographic factors	✓	✓	✓	✓	✓	✓
Cost of living metrics	✓	✓	✓	✓	✓	✓
Socioeconomic factors	✓	✓	✓	✓	✓	✓
R-squared	0.930	0.930	0.930	0.930	0.930	0.930
F statistics	977.844	1232.551	1171.246	1328.836	2024.858	1619.925
Observations	894	894	894	849	849	849

Notes. Percentage of insurance coverage is a binary indicator denoting top portion of the distributional split, where the percentile of each split is defined at the top of the column. Models 1 to 3 are FE regressions (state and year-quarter), Models 4 to 6 are control function regressions with same FEs. Robust standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

The second method relies on a covariate matching technique to select campaigns from the non-bankrupt pool that resemble campaigns from the bankrupt pool in terms of target amount, number of words in campaign description, campaign launch year and month to the matched campaigns.⁹ We compare the percentage of the target amount raised from each group using a t-test. Results of this check are reported in Table 5. Across both the random sample and the covariate-matched sample of campaigns with non-bankrupt owners, we see that the campaigns from bankrupt owners consistently hold lower fundraising success than campaigns from non-bankrupt owners. This test provides further confidence that the results above did not arise spuriously.

Secondary Analyses

Next, we perform additional analyses to understand the economic relationship of medical crowdfunding with respect to public health insurance coverage. More specifically, we examine the moderating effect of the coverage of Medicare and Medicaid on the impact of crowdfunding. For this set of tests, we conduct both fixed effects regressions and IV fixed effect regression. The results of this analysis are shown in Table 6. Across Models 1 to 3 in Table 6, the main effect of *AmountRaised_{it}* remains negative and significant, while the insurance coverage indicators are negative but not statistically significant across different splits. We further note that interaction term β_4 is not significant in the median and upper quartile specifications, but is positive and significant in the top decile specification (Model 3). The positive coefficient suggests that the crowdfunding effect in states with higher insurance coverage, relative to states with lower public health insurance coverage, tend to have a positive impact on bankruptcy levels, that is, a weakened ability to reduce bankruptcy. Such a result indicates that medical crowdfunding and public health insurance are substitutes in terms of reducing bankruptcies. More specifically, the coefficient implies that the presence of health insurance coverage can result up to 4.2 individuals substituting away from medical crowdfunding.

Furthermore, we note that this substitution effect is only present in states with extremely high levels of public health insurance coverage (i.e., over 36% coverage). This result suggests that crowdfunding is broadly beneficial in reducing bankruptcy rates, except in those regions where public health insurance coverage is widely available. A clear example of a jurisdiction falling into the top decile is the state of Massachusetts, which effectively provides near universal healthcare coverage to its residents. To check if this set of results persists after controlling for endogeneity, we re-estimate Equation 2 employing a control function approach in Models 4 to 6. The idea behind the control function correction is to derive a proxy variable that conditions on the part of y that depends on the error term. By performing this step, the remaining variation in the endogenous variable becomes independent of the error and a standard OLS estimator will be consistent (Louvriere et al. 2005; Petrin and Train 2009; Villas-Boas and Winer 1999). To that end, we address potential endogeneity in the main effect and interaction term involving *AmountRaised*, by including residuals from a first stage regression of bankruptcy levels on our independent variables and page view instrument, as an additional covariate. The results of these specifications are qualitatively similar to those in Models 1 to 3, giving us further assurance that these results are robust against endogeneity.¹⁰

Discussion & Limitations

This study investigates the impact of medical crowdfunding on bankruptcy levels in the U.S. Through the use of a series of empirical methods that account for various estimation biases and validity threats, we find that crowdfunding for medical expenses bring about a significant reduction in bankruptcy filing rates. Importantly, these study results are robust to a variety of model specifications and estimators. Using estimates from our IV models, we extrapolate the state-level effect to the national level using population size as a scaling factor, under the simplistic assumption that usage and donation levels are constant across

⁹ The matching procedure was executed using one-to-one nearest neighbor criteria with no replacement.

¹⁰ We note that the residual from the control function specification is statistically significant. This means that endogeneity is present in the OLS specification, and that the control function specification has successfully accounted for this.

all states. We find that if \$1,000 were raised in each state within a three-month period, this would reduce between 114 and 136 bankruptcies in the United States per quarter.

We further extrapolate the impact of the coefficient on amount raised to the overall benefit derived from all donations solicited on GiveForward. On average, GiveForward raises close to \$774,200 in donations for medical expenses in a given quarter. Scaling our coefficient estimates by a factor of 774, we observe that the donations from the crowdfunding platform are able to reduce approximately 4,644 bankruptcy cases in the country. This figure represents 3.9 percent of all Chapter 7 bankruptcies that are filed due to medical expenses.¹¹ Though the impact is modest relative to entirety of the U.S. bankruptcy market, crowdfunding's positive contribution towards bankruptcy reduction suggests that the phenomenon should perhaps be encouraged further, whether through federal policy measures or direct government support in the form of subsidies. Furthermore, the estimated benefit calculated here accrues to only one crowdfunding platform; the aggregate impact of all existing medical crowdfunding sites may be much larger and economically important. As recent work on donation-based crowdfunding of public goods has noted the likely benefits of matched contributions and seed funds (Burtch et al. 2013b), it will be interesting to consider ways of maximizing these benefits in future work, by encouraging interest towards crowdfunding activity. As noted before, the primary benefits we observe from crowdfunding are likely to be strongest amongst patients who lie at the margin, along the indifference curve, wherein the net benefit gained from bankruptcy filing is the lowest. For these individuals, even a few hundred dollars is sufficient to sway their decision away from bankruptcy filing. However, it is possible that a large fraction of the medical bankruptcy population is comprised of patients whose debts imply a much greater net financial benefit from bankruptcy. If this were the case, we would find it more difficult to cover their costs solely via crowdfunding efforts.

We further note a substitution effect between medical crowdfunding and public health insurance in our additional tests. This substitution effect only sets in at states with high levels of Medicare and Medicaid coverage. Such an observation provides further practical inputs for government and healthcare policies that are related to medical crowdfunding. Given that both medical crowdfunding and existing public health insurance schemes hold substitutive effects on each other, it might be socially beneficial to extend the eligibility constraints of public health insurance towards a wider population group, so as to minimize the level of overlap with the beneficiaries served by medical crowdfunding. In particular, such a strategy would be most useful for states that are already enjoying a large proportion of public health insurance coverage. An alternative approach would be to publicize medical crowdfunding and encourage its usage. Given that medical crowdfunding is a relatively new phenomenon, public awareness and willingness to donate via the platform may be limited. It may be worthwhile to consider official endorsements and legalization of medical crowdfunding to generate greater interests and assurance towards making donations on such platforms.

Beyond policy level interventions, it is quite likely that within platform efforts could also be undertaken to drive increases in crowdfunder contributions. Numerous studies have examined the dynamics of crowdfunding contributions, offering insight into the nuances of fundraising success. It is likely that many of those results could be applied at GiveForward and other, similar platforms, in an effort to boost fundraising outcomes. For example, past work has commented on the role of funding durations, targets and campaign 'pitch' content (Burtch et al. 2013b; Mollick 2014). Other recent work has considered the roles of interpersonal similarity between donors and recipients (Burtch et al. 2014a; Galak et al. 2011), as well as notions of community participation and reciprocity as drivers of fundraising success (Zvilichovsky et al. 2013). In each case, transferrable insights can be identified and applied on medical crowdfunding.

At the same time, in order to optimize impact, future work should also be undertaken to obtain a more precise evaluation of the mechanism underlying the relationship between crowdfunding success and bankruptcy filing rates. First, although we have identified a significant, negative relationship, in general, it remains possible that the relationship is subject to a number of moderating conditions. As an example, it may be that crowdfunding will be more effective in reducing bankruptcy amongst individuals who have not previously filed for bankruptcy, given that they will be less comfortable with this outcome and thus

¹¹ There are 189,000 Chapter 7 filings in the first quarter of 2013 across the U.S. Using the estimated proportion of medical related bankruptcies from Himmelstein et al. (2009), it is calculated that there are approximately 117,000 cases of medical-related bankruptcies filed in each quarter.

will be more likely to employ any donations more efficiently. Further, individuals' basic willingness to file for bankruptcy, if greater in certain regions, may imply a reduced concern for efficient use of funds, because patients in those regions may be more likely to view bankruptcy as an acceptable fall back plan. Accordingly, we might expect to see regional variation in the effectiveness of crowdfunding in reducing medical bankruptcy. These expectations are both driven by the aforementioned work that has discussed the social acceptability of personal bankruptcy (White 1998), which may be impacted by the prevalence of advertising for bankruptcy filing services or regional variation in general around the norms for bankruptcy filing (Lefgren and McIntyre 2009).

Second, here, we have focused on the contemporaneous impact of fundraising activities on bankruptcy filing prevalence. However, it is quite likely that the dynamics of injury, illness, fundraising and treatment may interact in important, interesting ways, influencing the rate of bankruptcy filing in future periods. For example, it may be that crowdfunding eliminates some bankruptcies entirely, but that it simply delays others to a later point in time. Alternatively, it is possible that fundraising success at GiveForward reduces the probability of bankruptcy for a focal individual, but that this in turn may drive a subsequent increase in the probability of supporting donors then filing for bankruptcy in the future. For example, if donors experience a decline in personal wealth from giving (e.g., if they are tapping into their savings), they may find it more challenging to absorb an unexpected financial shock in the future. Thus, we might observe a form of bankruptcy cascade or ripple effect.

Conclusion

In this work, we have examined the relationship between crowdfunding for healthcare expenses and the incidence of personal bankruptcy filing, with the goal of obtaining insight into the potential for crowdfunding to address unmet healthcare costs. We find that crowdfunding has a significant impact, reducing the incidence of personal bankruptcy filing. We establish the robustness of this result via the application of numerous alternative estimators and model specifications. In addition, we pursue a more nuanced understanding of the identified relationship by focusing on the moderating effects of public health insurance. Our findings have broad implications for the literature on IT in healthcare, the literature pertaining to treatment costs, health coverage and insurance, as well as the growing literature on crowdfunding. The results indicate that crowdfunding offers a viable stopgap measure for covering treatment costs, effectively allowing patients to tap into the wealth of their online social network. This is notable, as a number of recent studies in the crowdfunding literature have provided evidence of the importance of social ties, social capital and social networks in crowdfunding (Agarwal et al. 2011; Lin et al. 2013; Mollick 2014).

Our study focuses on a donation-based platform. However, other models have been developed in the crowdfunding space that might also see fruitful application to medical treatment costs. In particular, a loan- or micro-finance based model might be suitable here, as this could provide patients with a potentially low-cost alternative to formal loans. A reward-based crowdfunding model might allow patients to offer their personal skills or knowledge in exchange for contributions. Finally, even equity-based models have arisen recently that might be useful here. One notable example is Upstart, a platform that allows individuals to invest in others, and receive a fraction of their future earnings as compensation over subsequent years. Such a model here might allow patients to trade their future earnings for immediate funds, when needed. We have offered here the first empirical examination of crowdfunding's application to the area of medical treatment costs. However, it is our hope that our work can form a 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.

References

- Agarwal, A., Catalini, C., and Goldfarb, A. 2011. "Entrepreneurial Finance and the Flat-World Hypothesis: Evidence from Crowd-Funding Entrepreneurs in the Arts," *NBER Working Paper*.
- Agarwal, A., Catalini, C., and Goldfarb, A. 2013. "Some Simple Economics of Crowdfunding," in *Innovation Policy and the Economy*. University of Chicago Press.
- Agarwal, R., Animesh, A., and Prasad, K. 2009. "Social Interactions and the "Digital Divide": Explaining Variations in Internet Use," *Information Systems Research* (20:2), pp. 277-294.
- Agarwal, R., Gao, G., DesRoches, C., and Jha, A.K. 2010. "The Digital Transformation of Healthcare: Current Status and the Road Ahead," *Information Systems Research* (21:4), pp. 796-809.
- Ahlers, G.K.C., Cumming, D., Gunther, C., and Schweizer, D. 2012. "Signaling in Equity Crowdfunding," *SSRN Working Paper*.
- Allison, P.D., and Waterman, R.P. 2002. "Fixed-Effects Negative Binomial Regression Models," *Sociological Methodology* (32:1), pp. 247-265.
- Andreoni, J. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence," *Journal of Political Economy* (97:6), pp. 1447-1458.
- Angelucci, M., Karlan, D., and Zinman, J. 2013. "Win Some Lose Some? Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco," *Working Paper*.
- Ausubel, L.M. 1997. "Credit Card Defaults, Credit Card Profits, and Bankruptcy," *The American Bankruptcy Law Journal* (71), pp. 249-270.
- Bonfadelli, H. 2002. "The Internet and Knowledge Gaps: A Theoretical and Empirical Investigation," *European Journal of Communication* (17:1), pp. 65-84.
- Boyce, A., and Rainie, L. 2002. "Online Job Hunting," Pew Internet and American Life Project, Washington, DC.
- Burtch, G., Di Benedetto, C.A., and Mudambi, S.M. 2013a. "Leveraging Information Systems for Enhanced Product Innovation," in *E-Business Strategic Management*, F.J. Martinez Lopez (ed.). Springer.
- Burtch, G., Ghose, A., and Wattal, S. 2013b. "An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets," *Information Systems Research* (24:3), pp. 499-519.
- Burtch, G., Ghose, A., and Wattal, S. 2014a. "Cultural Differences and Geography as Determinants of Online Pro-Social Lending," *MIS Quarterly* (38:3), pp. 773-794.
- Burtch, G., Ghose, A., and Wattal, S. 2014b. "The Hidden Cost of Accommodating Crowdfunder Privacy Preferences: A Randomized Field Experiment," *Management Science*, Forthcoming.
- Carvajal, M., García-Avilés, J.A., and González, J.L. 2012. "Crowdfunding and Non-Profit Media," *Journalism Practice* (6:5-6), pp. 638-647.
- Chan, J., and Ghose, A. 2013. "Internet's Dirty Secret: Assessing the Impacts of Online Intermediaries on HIV Transmission," *MIS Quarterly*, Forthcoming.
- Currie, J., and Gruber, J. 1996. "Health Insurance Eligibility, Utilization of Medical Care, and Child Health," *The Quarterly Journal of Economics* (111:2), pp. 431-466.

- Desiraju, R., Nair, H., and Chintagunta, P. 2004. "Diffusion of New Pharmaceutical Drugs in Developing and Developed Nations," *International Journal of Research in Marketing* (21:4), pp. 341-357.
- Domowitz, I., and Sartain, R. 1999. "Determinants of the Consumer Bankruptcy Decision," *The Journal of Finance* (54:1), pp. 403-420.
- Fay, S., Hurst, E., and White, M.J. 2002. "The Household Bankruptcy Decision," *The American Economic Review* (92:3), pp. 706-718.
- Fichman, R.G., Kohli, R., and Krishnan, R. 2011. "The Role of Information Systems in Healthcare: Current Research and Future Trends," *Information Systems Research* (22:3), pp. 419-428.
- Gaggioli, A., and Riva, G. 2008. "Working the Crowd," *Science* (321), pp. 1443.
- Galak, J., Small, D., and Stephen, A. 2011. "Micro-Finance Decision Making: A Field Study of Prosocial Lending," *Journal of Marketing Research* (48:Special Issue), pp. S130-S137.
- Gross, T., Notowidigdo, M.J., and Wang, J. 2012. "Liquidity Constraints and Consumer Bankruptcy: Evidence from Tax Rebates," *NBER Working Paper*.
- Gruber, J. 2008. "Covering the Uninsured in the U.S.," *NBER Working Paper*.
- Hargittai, E., and Hinnant, A. 2008. "Digital Inequality: Differences in Young Adults' Use of the Internet," *Communication Research* (35:5), pp. 602-621.
- Himmelstein, D., Thorne, D., Warren, E., and Woolhandler, S. 2009. "Medical Bankruptcy in the United States, 2007: Results of a National Study," *The American Journal of Medicine* (122:8), pp. 741-746.
- Himmelstein, D., Warren, E., Thorne, D., and Woolhandler, S. 2005. "Marketwatch: Illness and Injury as Contributors to Bankruptcy," *Health Affairs* (Web Exclusives), pp. W5:63-W65:73.
- Howard, P.E.N., Rainie, L., and Jones, S. 2001. "Days and Nights on the Internet: The Impact of Diffusing Technology," *American Behavioral Scientist* (45:3), pp. 383-404.
- Kim, K., and Hann, I. 2013. "Does Crowdfunding Democratize Access to Capital? A Geographical Analysis," in: *INFORMS Conference on Information Systems and Technology (CIST)*. Minneapolis, MN.
- Landers, R.M. 2012. "The Dénouement of the Supreme Court's Aca Drama," *New England Journal of Medicine* (367:3), pp. 198-199.
- Lefgren, L., and McIntyre, F. 2009. "Explaining the Puzzle of Cross-State Differences in Bankruptcy Rates," *Journal of Law and Economics* (52:2), pp. 367-393.
- Lin, M., Prabhala, N., and Viswanathan, S. 2013. "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending," *Management Science* (59:1), pp. 17-35.
- Livshits, I., MacGee, J., and Tertilt, M. 2007. "Consumer Bankruptcy: A Fresh Start," *The American Economic Review* (97:1), pp. 402-418.
- Loges, W.E., and Jung, J. 2001. "Exploring the Digital Divide: Internet Connectedness and Age," *Communication Research* (28:4), pp. 536-562.

- Louviere, J., Train, K., Ben-Akiva, M., Bhat, C., Brownstone, D., Cameron, T.A., Carson, R.T., Deshazo, J.R., Fiebig, D., Greene, W., Hensher, D., and Waldman, D. 2005. "Recent Progress on Endogeneity in Choice Modeling," *Marketing Letters* (16:3-4), pp. 255-265.
- Lusardi, A., Schneider, D.J., and Tufano, P. 2011. "Financially Fragile Households: Evidence and Implications," *NBER Working Paper*.
- Madden, M. 2003. "America's Online Pursuits," Pew Internet and American Life Project, Washington, DC.
- Manning, W.G., Newhouse, J.P., Duan, N., Keeler, E., and Leibowitz, A. 1987. "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment," *The American Economic Review* (77:3), pp. 251-277.
- Mollick, E. 2014. "The Dynamics of Crowdfunding: An Exploratory Study," *Journal of Business Venturing* (29:1), pp. 1-16.
- Mossberger, K., Tolbert, C.J., and Stansbury, M. 2003. *Virtual Inequality: Beyond the Digital Divide*. Washington, DC: Georgetown University Press.
- Ordanini, A., Miceli, L., Pizzetti, M., and Parasuraman, A. 2010. "Crowd-Funding: Transforming Customers into Investors through Innovative Service Platforms," *Journal of Service Management* (22:4), pp. 443-470.
- Park, A. 2012. "Crowdfunding a Cure," *Time* (180:23), pp. 22.
- Petrin, A., and Train, K. 2009. "A Control Function Approach to Endogeneity in Consumer Choice Models," *Journal of Marketing Research* (47:1), pp. 3-13.
- Roberts, R.D. 1984. "A Positive Model of Private Charity and Public Transfers," *Journal of Political Economy* (92:1), pp. 136-148.
- Rose-Ackerman, S. 1996. "Altruism, Nonprofits, and Economic Theory," *Journal of Economic Literature* (34:2), pp. 701-728.
- Shah, V., Kwak, N.R., and Holbert, L. 2001. "'Connecting" and "Disconnecting" with Civic Life: Patterns of Internet Use and the Production of Social Capital," *Political Communication* (18:2), pp. 141-162.
- Sisler, J. 2012. "Crowdfunding for Medical Expenses," *Canadian Medical Association Journal* (184:2), pp. E123-E124.
- Villas-Boas, J.M., and Winer, R.S. 1999. "Endogeneity in Brand Choice Models," *Management Science* (45:10), pp. 1324-1338.
- Wheat, R.E., Wang, Y., Byrnes, J.E., and Ranganathan, J. 2013. "Raising Money for Scientific Research through Crowdfunding," *Trends in Ecology & Evolution* (28:2), pp. 71-72.
- White, M.J. 1998. "Why Don't More Households File for Bankruptcy?," *The Journal of Law, Economics & Organization* (14:2), pp. 205-231.
- Wilper, A.P., Woolhandler, S., Lasser, K., McCormick, D., Bor, D.H., and Himmelstein, D. 2009. "Health Insurance and Mortality in Us Adults," *American Journal of Public Health* (99:12), pp. 2289-2295.
- Zvilichovsky, D., Inbar, Y., and Barzilay, O. 2013. "Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms," *SSRN Working Paper*.