View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Concordia University Research Repository

Success Factors in Healthcare Crowdfunding

Qiao Nie

A Thesis

In

The John Molson School of Business

Presented in Partial Fulfillment of the Requirements

for the Degree of Master of Science in Administration (Finance) at Concordia University

Montreal, Quebec, Canada

March 2018

© Qiao Nie, 2018

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: Qiao Nie

Entitled: Success Factors in Healthcare Crowdfunding

and submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN ADMINISTRATION (FINANCE)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final Examining Committee:

____Chair
Dr. Bianca Grohmann

____Examiner
Dr. Tingyu Zhou

____Examiner
Dr. Matthäus Tekathen

____Supervisor
Dr. Denis Schweizer

Approved by ____
Graduate Program Director

____
Dean of Faculty

Date ________________________ March 29, 2018__________________________

Success Factors in Healthcare Crowdfunding

Qiao Nie

ABSTRACT

Through overseas healthcare crowdfunding, many patients from developing countries successfully collect enough money for their treatments. Knowing the importance of this alternative financing tool, we studied the factors that affect the speed of healthcare crowdfunding. Timing — that is whether the campaigns were posted before, during or after American holidays — is significantly associated with a higher funding speed. Concerning macroeconomic conditions, if two patients hold the same characteristics except for their home countries, the one from poorer country statistically completes the campaign faster than the other. Moreover, the larger portion of universal funders[1] the campaigns have, the faster the patients obtain the predetermined funding amount with the other variables remaining constant. Similarly, a higher percentage of active funders with profile pictures or name initials is associated with a faster funding speed. Furthermore, pictures with patients smiling attract a greater percentage of active funders to donate, which positively affects the funding success in the long term.

[1] The universal funders: the funders contribute to the crowdfunding platform; then the platform distributes to the specific campaigns.

ACKNOWLEDGMENT

I wish first to express my sincere appreciation to my thesis supervisor Dr. Denis Schweizer. He provided me with endless help whenever I ran into troubles or had a question about my research. All through the whole process of writing the thesis, he consistently motivated me to have my own work, but also contributed to the progress of the paper with precious ideas. I would also like to thank my thesis committee Dr. Tingyu Zhou and Dr. Matthäus Tekathen for their insightful feedback and recommendations.

Secondly, I would also like to thank the web crawling expert Xiao Ma who was involved in the data collection for this thesis. Without his dedicated input, the data could not have been successfully coded and organized for the empirical study.

Finally, I must express my profound gratitude to my parents and to my husband for supporting me throughout the master degree study. In addition, I appreciate that my friends gave me continuous encouragement when it was a particularly hard time at the last stage of writing the thesis. This accomplishment would not have been possible without them.

Table of Contents

List of Tables and Figures

List of Tables

List of Figures

Success Factors in Healthcare Crowdfunding

1. Introduction

A World Health Organization (WHO) and World Bank Group report[2] published on June 12, 2015, showed that 400 million people do not have access to essential health services. Currently, due to spending on healthcare services, 6% of people in low- and middle-income countries (LMIC) are tipped into or pushed further into extreme poverty (a disposable income of $ 1.25/day). WHO stated that people need to be protected from being pushed into poverty because of cost of treatments.

The health insurance system is mature in developed countries; however, the coverage is much less widespread in developing countries in Africa, Asia, and Central America. The available interventions include subsidies for routine outpatient care, specific disease programs, hospital insurance, and services targeted at the chronically poor and socially excluded (Peter et al., 2008). However, the effective interventions are not fully exploited due to both the severe poverty and the failure of social healthcare insurance. Therefore, healthcare crowdfunding (HCCF) serves as a strong alternative tool in this situation. Basically, HCCF uses collective decision making via a social media platform to evaluate and raise financing for new projects (Bruton, Khavul, Siegel, & Wright, 2015). It reduces the geographic limitation (Agrawal, Catalini, & Goldfarb, 2011) by enabling home funders and overseas funders to participate in campaigns (Günther, Johan, & Schweizer, 2018). The idea behind HCCF is that it gets crowds involved in helping with people's medical bills by running campaigns. HCCF in the United States has evolved into a cottage industry, where several mature HCCF platforms were launched in the past ten years, such as Watsi, GoFundMe, and Youcaring.

Our research is based on a healthcare crowdfunding website named Watsi. Founded in May 2010, Watsi[3] is a US crowdfunding platform in the global healthcare area, in which 100% of donations go to patients' medical treatment. This crowdfunding platform works with non-profit healthcare providers[4] in 24 countries, including Cambodia, Nepal, Guatemala,

[2] Joint WHO/ World Bank new release: http://www.who.int/mediacentre/news/releases/2015/uhc-report/en/
[3] The introduction of Watsi's donation process and its website are provided in the appendix.
[4] These healthcare providers are called medical partners.

Ethiopia and so on. Fortunately, all of the campaigns on Watsi achieved their funding goals, which means we cannot use "complete" or "not complete" to measure the outcome. Instead, we use the time spent on being fully funded as a measure of success. The less time a campaign used to complete the funding, the more successful the campaign would be. Watsi actively controls the stream of new campaigns by first keeping campaigns in their backlog and only posting them when there are extra donating demands. Therefore, we do not need to control for the competition among campaigns (Ly & Mason, 2012) because Watsi has the right balance of supply and demand. With hazard rate model and propensity score matching, we investigated the factors that could affect the success of the campaign. We did a comprehensive analysis of the healthcare crowdfunding mechanism using 4677 campaigns from 2012 to 2016.

This study conducts the first-ever quantitative analysis of the healthcare donation-based crowdfunding. Taking a deep dive into the campaigns on Watsi, we found that there are several influential factors for the success of HCCF. Timing (Agrawal, Catalini, & Goldfarb, 2015) and funder specific features (Gerber, Hui, & Kuo, 2012) are important factors determining the crowdfunding outcome. Posting a campaign near a holiday helps the campaign's success, which means that Watsi can post more campaigns before, during or after a holiday to raise the average funding speed. Given that the home countries vary among the patients, we also found that a campaign from a poorer country with a lower GDP per capita is linked to a higher speed. In terms of funders' characteristics, a larger portion of universal funders is associated with a faster funding speed due to the signaling effect; therefore, Watsi can contribute to more campaigns during the early days, serving as a positive signal to the following funders. Active funders with pictures or initials positively affect the funding success; accordingly, to replicate the positive effect of these active funders, Watsi can increase its presence on social media to attract more funders. In addition, the patients' facial expressions also relate to funding success in the long term, given that pictures with patients smiling attracts a larger portion of active funders, especially the ones with initials.

The structure of this study is as follows: section 2 summarizes the literature and formulates the testable hypotheses. Section 3 goes through the methodologies that we used in this study. Section 4 shows the descriptive statistics, and section 5 explains the results of the regressions. Section 6 introduces the limitations of this study and the possible directions future researchers can take. Last but not the least, section 7 reviews the findings obtained from the qualitative and quantitative analysis.

2. Literature Review

Healthcare systems in developing countries are not properly functioning and causing more severe poverty; hence overseas HCCF can provide necessary help. In LMICs, financial access (or affordability) is the most important perspective and is directly associated with the dimensions of poverty (Peter et al., 2008). However, a tax-funded health system is not easy to build due to the lack of a robust tax base and a low institutional capacity to collect the taxes (Carrin, Waelkens, & Criel, 2005). With regard to solving financing problems, different types of crowdfunding have been implemented for the different projects, including reward crowdfunding for innovative products (Mollick, 2014), equity crowdfunding for entrepreneurs (Ahlers, Cumming, Günther, & Schweizer, 2015), and real estate crowdfunding for property developers (Schweizer & Zhou, 2017). Although HCCF has not been discussed widely, it has accomplished so much in the healthcare system. For example, in the United States, Youcaring has raised $800 million for personal medical and charitable causes; with more than 50 million funders, campaigns have raised over $5 billion funds on Gofundme. Thanks to the development of crowdsourcing through Web 2.0 (Brabham, 2008; Kleemann, Voß, & Rieder, 2008) and non-profit organizations dedicated to healthcare in developing countries, the global HCCF is reducing the geographic limitation and providing a faster way to finance healthcare overseas with the money collected online. In contrast to the other types of crowdfunding which contain some possibility of fraud (Cumming, Hornuf, Karami, & Schweizer, 2016), there is low uncertainty related to fraud funding on Watsi given the close collaboration between the HCCF platform and local medical partners.

The fundraisers and funders face information asymmetry during the process of HCCF (Belleflamme, Lambert & Schwienbacher, 2014) because fundraisers do not know which funders are interested, and at the same time funders do not know whose needs are more urgent. Looking for the factors affecting funding speed is essentially finding a way to decrease information asymmetry, which could increase the funding efficiency. The factors in the literature can be divided into three categories: project-specific, fundraiser-specific and funder-specific.

Possible influential project-specific factors include project goal, project duration, and video presence (only if the video show is an option for the fundraisers) (Mollick, 2014). Based on the literature, we included project goal, which is the cost of treatment, into our predictive analysis. In addition, linguistic styles boost the success of social crowdfunding campaigns (Parhankangas & Renko, 2017), and whether the campaign is narrated as helping others or a business opportunity also causes the lenders to have a different attitude in their response (Allison, Davis, Short, & Webb, 2014). Nevertheless, since all of the campaign descriptions are written by the professionals working for Watsi and usually one team is taking care of all of the campaigns in a specific country, we only consider country differences. Moreover, timing is also a crucial factor for campaigns' success (Agrawal et al., 2015). Our timing measure is if the crowdfunding posts before, during, or after American holidays. As stated by the data from Sanvine, a company that is specialized in tracking web traffic, the internet usage was higher than normal during Christmas holiday in 2013. The festivals, namely Christmas, Easter, Thanksgiving, and New Year's Day, convey the emotion of happiness, appreciation, and warmth. In addition, spiritual activities, including charity (HCCF), may help people feel more satisfied (Kasser & Sheldon, 2002). Therefore, we propose that:

> *Hypothesis 1: Campaigns posted before, during, or after holidays are associated with a higher speed.*

Next, the fundraisers' features also make a difference in the crowdfunding speed. In the reward/equity crowdfunding, the entrepreneurs need to have multiple skills to be successful (Lazear, 2004). More Facebook connects and more quick updates for projects lead to a higher probability to succeed (Mollick, 2014). Unfortunately, on Watsi, patients are not able to directly communicate with the funders; instead, medical partners update recovery progressions on behalf of the patients. Given the special features of healthcare crowdfunding, we checked if the patients' age and gender are influential to the funding speed. Furthermore, since most of the funders are from the US where medical expenses are the leading cause of bankruptcy — 62% of the personal bankruptcies were reported due to medical bills (Burtch & Chan, 2014) — we assume that the funders take the macroeconomic conditions of patients' home countries into consideration. Therefore, we initiated the hypothesis that:

> *Hypothesis 2: Campaigns from countries with lower GDP per capita need less time to finish on average with the other features constant.*

Funders' incentive and characteristics are also discussed in the literature as important factors. The researches show that social information (i.e., other crowdfunders' funding decisions) plays a key role in the success of a project (Kuppuswamy & Bayus, 2018; Moisseyev, 2013). In some reward platforms, the contributions received during the early days of a campaign accelerate its success (Colombo, Franzoni, & Rossi-Lamastra, 2015); the primary funders, who usually have funding experiences (Agrawal et al., 2015), are positive signals in the signaling theory. Some funders may donate to a campaign to feel involved in entrepreneurial initiatives (Schwienbacher & Larralde, 2010). However, as a result of the bystander effect, some people would not contribute when other funders have already donated (Kuppuswamy & Bayus, 2018). Correspondingly, the typical pattern of project support is U-shaped, which means funders are more likely to contribute to a project in the first and last week as compared to the middle period of the funding cycle (Kuppuswamy & Bayus, 2017). On Watsi, some funds are directly distributed to existing campaigns when these campaigns are first posted (the details are not disclosed). We would like to test whether those universal funders also have the signaling effect:

> *Hypothesis 3: Campaigns with a larger percentage of universal funders tend to complete within a shorter time period.*

In addition to the potential signaling effect of universal funders, the characteristics of the active funders[5] also indicate the funding speed. People's profile on social media can be used to accurately predict their personality (Golbeck, Robles & Turner, 2011). Usually, the extroverted individuals would have a larger number of friends and would belong to more

[5] In this study, active funders refer the funders who make the donation decisions by themselves instead of give the right to Watsi (as an universal funders)

Facebook groups than the introverted ones (Ross et al., 2009; Amichai-Hamburger & Vintzky, 2010). Moreover, normative behavior is less informative about an individual's personality than relatively non-normative behavior (Jones & Davis, 1965; Pelled et al., 2017). Therefore, the funders who actively donate and post their profile pictures/names (non-normative behavior) tend to be extroverted; they would be more likely to raise awareness of the campaigns among their social media networks. Based on this theory, we propose that:

> *Hypothesis 4: The higher percentage of active funders with pictures or initials, the faster patients get enough funds for their treatment.*

Due to special features of HCCF, we highlight factors of facial expression and life-threatening key words in section 5.4 and 5.5 of this study. Unlike reward and equity crowdfunding in which funders spend most of their time evaluating products or companies respectively, HCCF involves more personal interactions between patients and funders. Psychologically, individuals who smile are rated as higher in kindness and honesty (Thornton, 1943) and are more likely to be attributed to positive traits (Palmer & Simmons, 1995). On the other hand, sympathy was found to be positively related to helping in philanthropy (Eisenberg, et al., 1989). In addition to the urgency level of the patients' health situation, funders may also take patients' personality into consideration and show more sympathy to the kind and honest people based on profile pictures. Furthermore, people have a higher willingness to help others if they believe their contribution really matters (Kuppuswamy & Bayus, 2017). The optimistic patients are more likely to rebuild their happy lives after their recovery and, in return, contribute to their communities. Since the only pictures on campaign pages are the patients' profile pictures, we would like to investigate if the patients' smile affects the funding speed.

> *Hypothesis 5: If the patients smile in their profile pictures, the campaign is more likely to finish faster holding the other factors constant.*

Finally, how the description is narrated could possibly affect the success of the campaign. Spelling errors indicate reduced preparedness and quality (Mollick, 2014); a longer description could be associated with a higher possibility to succeed (Koch & Siering, 2015). Moreover, the phrases used in the campaign descriptions have the power to predict the success of the campaign (Mitra & Gilbert, 2014). At the same time, sympathy plays an important role in a monetary donation (Lee & Chang, 2007) including HCCF; an identifiable victim (or situation) is more likely to evoke sympathy and move people to give (Small, Loewenstein & Slovic, 2007) compared to statistical figures. Thus, being recognized by the funders is crucial for campaigns' success. On Watsi, funders may recognize patients whom they would like to help by evaluating the urgency level of the patients' situation based on the campaign description; therefore, by means of life-threatening keywords, the platform may accelerate campaigns' success. Regarding this potential consequence, we propose the hypothesis that:

Hypothesis 6: Campaigns with life-threatening words in the description can finish faster with the other characteristics remaining constant.

Furthermore, we would also like to discuss the impact of the two factors above on the distribution of the different types of active funders. The evidence demonstrates that fundraisers are motivated to engage in crowdfunding given direct connection to the funders through a long-term interaction that extends beyond the moment of the financial transaction (Gerber et al., 2012). Likewise, in the long-term, the funders embrace the disciplined pursuit of financial returns, social returns, economic compensations and personal values (Moore, Westley, & Brodhead, 2012; Geobey, Westley, & Weber, 2012). In contrast to the universal funders, the active funders can directly obtain satisfaction from executing personal and social values upon the campaigns' success. Therefore, they are more likely to donate to the other campaigns and spread the word for Watsi and HCCF. This effect could improve the funding speed on average in the long term but might not reflect on the case level in the short term. In summary, we are interested in whether the campaign would be composed of a higher percentage of certain types of active funders, if the patients altered their facial expression or added life-threatening words.

Hypothesis 7: If the patients smiled, a larger fraction of total funders would be composed of: active funders in general, active funders with pictures, active funders with initials and active anonymous funders.

Hypothesis 8: If life-threatening words are present in campaign descriptions, a larger fraction of total funders would be composed of: active funders in general, *active funders with pictures, active funders with initials and active anonymous funders.*

Figure 1 summarizes success factors appearing in the literature supplemented with our unique testing factors.

[Insert Figure 1 Here]

3. Methodology

To detect the potential success factors, the researchers mainly applied the logistic model. They regressed the factors discussed above on a binary variable representing whether the projects successfully received the funds (Koch & Siering, 2015). Additionally, some innovators utilized machine learning to predict whether the funders would fully fund the projects (Greenberg, Pardo, Hariharan, & Gerber, 2013). However, on Watsi, all of the campaigns were backed with the total amount of campaign goals eventually, which means it is impossible to deploy logistic regression. Alternatively, we used the Cox proportional hazards model to analyze the expected time for campaigns to succeed (Lane, Looney, & Wansley, 1986; Shumway, 2001). In this study, the campaigns' success is considered as the same concept as terminating/failure in the original hazards model, for example the death of the patients or the bankruptcy of the corporations. Finally, to better determine the effect of facial expression and life-threatening words on the active funders' distribution of the campaigns, we utilized the propensity score matching analysis (Jalan & Ravallion, 2003; Lechner, 2002; List, Millimet, Fredriksson, & McHone, 2003).

3.1 Hazard Rate Model

The Cox proportional hazards model is a semi-parametric model where the baseline hazard is allowed to vary with time (Stevenson & EpiCentre, 2009). Since the purpose of this study is to estimate the marginal effect of the certain factors which can affect the speed of the funding process, this model is suitable for testing our hypotheses. The multivariate Cox regression is heavily used in medical research (Sy & Taylor, 2000), and it also appears in the finance field, for example, the bankruptcy forecast (Shumway, 2001) and the mortgage termination study (Deng, 1997).

We followed the method used by Deng (1997), setting T as a continuous random variable that measures the duration of the campaign from being posted to completion. We presume that all of the campaigns would start at the same point and defined the survival function[6] as:

$$F(t) = P(T \geq t) \tag{1}$$

Then the distribution of failure times is called the probability density function (pdf) with the random variable t:

$$f(t) = \lim_{\Delta t \to 0^+} \frac{p(t \leq T < t + \Delta t)}{\Delta t} = \frac{-\,dF(t)}{dt} \tag{2}$$

Using this function, we described the hazard rate (or hazard function), an instantaneous rate of completing the campaign at $T = t$ conditional on survival to time T, as:

$$h(t) = \lim_{\Delta t \to 0^+} \frac{p(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{\frac{-\,dF(t)}{dt}}{F(t)} = \frac{f(t)}{F(t)} = \frac{-d\ In\ F(t)}{dt} \tag{3}$$

The Cox proportional hazard model (Cox & Oakes, 1984) was defined as follows:

$$h(t, \gamma) = h_0(t)\exp(\gamma(t)\beta) \tag{4}$$

In the equation above, γ is the vector of the factors that can affect the hazard rate; $h_0(t)$ is the baseline model; β is a vector of the parameter that we estimate with maximum likelihood method. This model depicts the exponential influence of the factors on hazard rate.

Correspondingly, the estimate function of this cox proportional hazard model can be written as:

$$h(t_i, \gamma) = h_0(t_i)\exp(\gamma(t_i)\beta)\,\varepsilon_i \tag{5}$$

In this equation, t_i can be any time point before a campaign censors. ε_i is a random error term. Moreover, hazard ratio measures the effect of the change of independent variables on the hazard rate. The regression model (6) treats the log of the hazard rate as a function

[6] The survival function is a function that measures the probability that an object of interest would survive beyond a given time.

of the log of a baseline hazard ($\log(h_0(t_i))$ and a linear combination of independent variables:

$$\log(h(t_i, \gamma)) = \log(h_0(t_i)) + \beta\gamma(t_i) + \varepsilon_i \quad (6)$$

However, in order to interpret the regression coefficients in terms of their economic meanings, this study transferred these coefficients back to hazard ratios given by e^{β}.

3.2 Propensity Score Matching

Propensity score matching (PSM) serves as an alternative to multivariate logistic regression (Rosenbaum & Rubin, 1983). Dividing the observations into subclasses by matching with their propensity score, we were able to estimate the unbiased treatment effect because, within each subclass, the observations are homogeneous (Zanutto, 2006).

To estimate the treatment effect, this study defined the average treatment effect (ATE) and identified the propensity score as a matching tool. If the treatment (smile or life-threatening word) did not occur, the outcome (funders' composition) was designated as y_{0i}; if the treatment occurred, the outcome was designated as y_{1i}. For any T_i, the treatment effect was thus defined as:

$$\tau = y_1 - y_0 \quad (7)$$

However, we cannot observe both y_{1i} and y_{0i}. Therefore, we use the ATE which measures the difference of the expected outcome between the treatment and control group.

$$ATE = E(\tau) = E(y_1|x, D = 1) - E(y_0|x, D = 0) \quad (8)$$

$D = 1$ indicates that the expected outcome is in the treatment group; $D = 0$ is the condition for the control group. To simulate the experiment, this study regressed the unobservable variables on the observable variables with the probit regression to obtain their propensity score.

$$p(x) = f(\ \alpha + \beta x) \quad (9)$$

x is the vector of the observable variables; β is the vector of parameters for the vector x. f (*) defines the cumulative distribution function of the standard normal distribution. Using maximum likelihood mechanism, we would be able to generate the probability $p(x)$. When we construct the subclasses with $p(x)$ and match the variables between treated and control groups within the subclasses, we follow two rules:

i. The covariates are balancing: the distributions of the covariates within the subclasses are the same (Rosenbaum & Rubin, 1983; Caliendo & Kopeinig, 2008);
ii. The average of the propensity score $p(x)$, the balancing score, must also be the same.

The nearest neighbor matching is applied to find the control observations for the corresponding treated observations. For each treatment observation i, we selected a control observation j that has the closest $p(x)$.

$$\min\left\|p_i(x) - p_j(x)\right\| \tag{10}$$

Then, we revised our average treatment effect function and adjusted the function with the propensity score matching.

$$ATE = E(\tau|p(x), D = 1) = E(y_1|p(x), D = 1) - E(y_0|p(x), D = 0) \tag{11}$$

A simple t-test between the outcomes for the treated and control groups was needed at the end to draw a conclusion.

3.3 Variable Description

[Insert Table 1 Here]

4. Descriptive Statistics

Our research is based on 4677 campaigns which were posted from June 22, 2012 until February 6, 2016. All of the patients received the total amount of funds for their treatment which had been predetermined by the medical partners based on the diagnosis of their diseases. According to figure 2, the slope is steep during the first 20 days (the probability of completing the campaign quickly increases once the campaign is posted); then, within 20 to 65 days, it becomes flat (the probability of completing a campaign does not change much even if we wait longer); and it surges at the end after around day 65 (the probability increases rapidly at the last stage). This pattern is consistent with the typical U-shaped pattern of project support. (Kuppuswamy & Bayus, 2018).

[Insert Figure 2 Here]

The patients' age ranges from 0 (newborn babies) to 90 years old with a mean age of 26 years old. The distribution of the population among the four groups (babies, children, adults and seniors) is displayed in figure 3. Children and adults comprise 75% of total patients; senior people account for 16% and babies make up for only 9%. At the same time, within the group of 4,178 patients whose gender is successfully coded, 58% of the patients are females; 42% of the patients are males, showing that women and children are more likely to seek medical attention.

[Insert Figure 3 Here]

To better demonstrate patient characteristics, we divided variables into numerical variables and dummy variables to display the descriptive statistics. According to table 2, the average time to finish a campaign (TIME) is 3.35 days, while the median is 1.92 days, meaning that over half of the campaigns finish within 2 days. The maximum cost of the treatment (CTREAT) is $3,000; while the average treatment funding sought by patients is only $500. The relatively low funding amount can be part of the reason why campaigns can finish within a short period. Moreover, because the funding goals were low, a small amount of funders participate in most of the campaigns. Specifically, 75% of the campaigns have less than 12 funders (NOTF), while 50% of the campaigns have less than 5 funders. With regard to funders' characteristics, on average, a campaign has 3.67 universal funders (NOUF), 4.54 funders with name initials (NOIF) (2.23 or 49% being active funders), and 1.81 funders with profile pictures (NOPF) (0.71 or 39% being active funders). To remove the effect of scale, we used the percentage of different types of funders to represent the number of specific types of funders. The amount of life-threatening words (LFTW) shows a high kurtosis with a low mean, meaning that most of campaign descriptions do not indicate a life-threatening situation of the patients. According to the World Bank, the average GDP per capita (GDPP) worldwide is $10,151. However, the lowest GDP per capita among the countries in this study is only $286 and 50% of countries have GDP per capita less than $1,095 which is only 10% of the world average.

[Insert Table 2 and Table 3 Here]

In addition to the numerical variables, table 3 shows the frequency of the dummy variables. In this study, 29% of the patients have a universal funder as their last funder (LFUF). In addition, our coding results suggest that 53% of the patients smile (SMILE) in the campaign pictures; and 20% of the patients have at least one life-threatening word (LFTW) in their campaign descriptions. Lastly, 39% of the patients live in the countries with a lower-than-average GDP per capita among the 24 countries in our sample.

The correlation among the variables is shown in table 4. Cost of treatment (CTREAT) relates significantly to multiple variables at 95% confidence level, including whether the patient smiles (SMILE) and the patient's age group (PAGE). Patients from countries with a lower GDP per capita are inclined to ask for smaller treatment fund, while attracting more from active funders who disclose their pictures and name initials. Patients smiling and life-threatening words are also significantly correlated to funder-based variables.

[Insert Table 4 Here]

In order to address our concern about potential multicollinearity, given a high correlation among the independent variables, we used variance inflation factor (VIF) to measure the degree of multicollinearity and determine whether some specific independent variables need to be excluded. In table 5, none of the variables have a VIF over 10 – a threshold widely used in statistic studies (Chatterjee & Price, 1991). Therefore, multicollinearity was not severe enough for us to drop any of the variables.

[Insert Table 5 Here]

5. Results

As we discussed in the methodology section, the higher the hazard rate, the higher the probability the campaign will be able to finish at a certain time point; in other words, the campaign will succeed faster. Since the hazard ratios, transformed from the coefficients, denote the direct effect on the hazard rate, we first explain the impact on hazard rate and then link it to the funding speed.

5.1 Basic Hazard Model

Starting from the basic hazard model, model (1) in table 6, we found that the cost of treatment (CTREAT) intensively affects the funding process. Similar to the literature, increasing the goal size is negatively associated with the success (Mollick, 2014; Kuppuswamy & Bayus, 2018). The higher cost the patients need to collect, the lower the hazard rate is. On average, the hazard rate decreases by 60% (1-0.4012) as compared to another campaign in which the medical treatment costs $1,000 more without any changes in the other variables. Therefore, the cost of treatment negatively impacts the funding speed. Secondly, the hazard rate varies significantly between the four groups: babies, children, seniors, and adults as the baseline. Compared to being an adult, if the patient is a baby (PAGE (Baby)), the hazard rate rises by 36%; if the patient is a child (PAGE (Child)), the hazard rate increases by 47%; finally, if the patient is a senior person (PAGE (Senior)), the hazard rate falls by 92%. The campaigns of babies or children complete at a higher speed, while the campaigns of seniors have a lower speed, holding the other factors constant. Gender (GDER) is also among our controls, but statistically, the impact is not significant at the confidence level of 90%. Moreover, as stated by Watsi, the platform distributes some funds to the existing campaigns on the first business day of each month, which is one of the mechanisms to help the universal funders execute their donation. Whether the campaign was posted on the first business day of a month (FBDAY) has a hazard ratio of 1.6675, suggesting that campaigns posted on the first business day have a hazard rate higher than that of the others by 67% on average. Therefore, being posted on the first business day of a month is positively related to the funding speed. If the last funder is a universal funder (LFUF), the hazard increases by 58%, indicating a higher funding speed. In addition, we control the influence of home countries of the patients and the year fixed effect.

[Insert Table 6 Here]

5.2 Testing Models about Timing and Economy Factors

In model (2) of table 6, we discovered some evidence to support hypothesis 1. If a campaign is posted on Watsi before, during or after one of the four important holidays (PADH), namely Christmas, New Year's Day, Easter, or Thanksgiving, the campaign wins a hazard rate which is 37% higher than the campaigns posted any other time, with the other variables constant at the confidence level of 99%. This statistic result indicates that people may intend to help others when they feel beloved and relaxed, and charity, in return, also makes them feel more satisfied (Kasser & Sheldon, 2002). This study implies that funders make the donating decision quicker when it is near a holiday.

The model (3) in table 6 is utilized to test hypothesis 2. The result indicates that funders consider the macroeconomic conditions of a patient's home country when they make the donation decision. If two patients have the same profile except for their home countries, the one from a poorer country (among the second half of the 24 countries) (GDPPR) has a higher hazard rate by around 27%, which is significant at the confidence level of 99%. In other words, the lower GDP per capita is associated with a higher funding speed. Usually, healthcare insurance provides a lower coverage in the less developed countries and governments are less capable of filling this gap in medical funds. In addition, it is highly possible that the intuitive understanding of poverty and the striking news about people's suffering lead the funders to donate faster. The statistic results support hypothesis 2: funders take the macro-economy into consideration when they select campaigns to support.

5.3 Testing Model about Funders' Proportion

In table 7, each funder's proportion has been incorporated in model (4). Since the universal funders' profile may also affect the funding speed, there are another two variables being controlled: percentage of funders with pictures (NOPF, %) and percentage of funders with initials (NOIF, %). Holding the other factors constant, the hazard rate would rise by 683% if a campaign consisted of 1% more universal funders. Therefore, we can reject the null hypothesis that the percentage of universal funders has no impact on funding speed at the confidence level of 99%. In other words, the percentage of universal funders is positively associated with a higher funding speed, providing some evidence to support hypothesis 3. Thus, the signaling effect is likely to play an important role in the funding process. Specifically, the funds distributed by Watsi to a campaign, immediately after the campaign is posted, serve as a positive signal that motivates other funders to make the decision to donate faster (Colombo, et al., 2015).

Furthermore, model (4) also indicates that if 1% more active funders with pictures (NOPFU, %) contributed to a campaign, the hazard rate would increase 2.64 times at 99% confidence level, which implies a higher funding speed. Similarly, the percentage of the active funders with initials (NOIFU, %) is also positively related to the funding speed: holding the other factors constant, a campaign with 1% more such kind of funders would have 4.65 times hazard rate as compared to the rest of the funders. Usually, active funders with pictures or initials are more extroverted than universal funders who do not make their own funding decisions and active anonymous funders who do not disclose their personal information. Thus, they would be more active on other social media including Facebook and Twitter (Amichai-Hamburger & Vintzky, 2010), which means a higher chance for them to share Watsi campaigns or other Watsi-related information directly on their social media or in their social media groups[7]. In other words, campaigns that obtain donations from more extroverted active funders would get exposure to potential funders on the internet. Generally speaking, the exposure significantly increases the probability to get fully funded within a short time period, which strongly supports hypothesis 4.

5.4 Facial Expression and Life-threatening Words

The parameter estimates in model (5) within table 7 suggest that whether a patient smiles in the profile picture (SMILE) is not significantly related to the funding speed. As the same as facial expression indicator, life-threatening words (LFTW) is not statistically significant either, which is not sufficient to support hypothesis 5 and 6. The insignificance may be caused by funders' different perception of smile and life-threatening words. Some funders, as we expected, may view smiling patients as kind and honest people who deserve healthcare, while some funders may interpret smile as unurgent. As the same as smile, life-threatening words may also be understood differently. Some funders may be more willing to donate to people whose situation is more severe, while some funders might not think their help for the life-threatening situation is worthwhile. As is discussed in model (4), because active funders not only donate to the specific patients, but also raise the awareness of Watsi and HCCF in public, they play a very important part on Watsi. Even though we cannot find a direct impact of "smile" and "life-threatening words" on the funding speed,

[7] Funders can directly share campaigns to Facebook and Twitter from Watsi.

they may influence the donation decision of active funders, which is tested with propensity score matching method in the next section.

[Insert Table 7 Here]

5.5 Average Treatment Effect of "Smile" and "Life-threatening Words"

To determine the potential impact of both "smile" and "life-threatening words" on active funders' decision-making, we conducted the propensity score matching method to estimate the treatment effect. Starting with "smile" as a treatment, we divided the patients into two groups: the treatment group (including patients smiling in the pictures) and the control group (including patients not smiling in the pictures). Before we built the propensity score, we obtained the descriptive statistics of covariates between the treated group and the control group including cost of treatment (CTREAT), patients' age (AGE), gender (GDER), GDP per capita (GDPP), whether the campaign is posted on the first business day of the month (FBDAY), whether the last funder is a universal funder (LFUF), whether the campaign is posted before, during or after a holiday (PAHD), and whether it has life-threatening words (LFTW).

[Insert Table 8 Here]

In table 8, we observed some different features between the treated group and the control group. The average cost of treatment in the treated group is $764, which is higher than that in the control group of $506. In addition, the GDP per capita of patients' home countries in the treated group, on average, is $1,220, which is lower than that in the control group of $1,608. Regarding the gender difference, girls are more likely to smile than boys. In terms of age, the patients in the treated group are 17 years younger than the individuals in the control group, which means that the smiling patients tend to be younger on average.

When we estimated the propensity score and matched the observations, we followed the procedure of Caliendo & Kopeinig (2008) to always assess the matching quality and iterate the process with different specifications if the assessment cannot be passed. The final assessment results indicate that only when we involve gender (GDER) and age category (PAGE), the balancing of the covariates are satisfied. According to the results from

STATA[8], four different blocks (or two subclasses) with non-differentiated mean propensity score are created for the treated and control groups. Table 9 shows the inferior bound of blocks and the number of observations in the treated and control groups.

[Insert Table 9 Here]

The results of probit regression in table 10 imply that at least one of the covariates' coefficients is significantly different from 0 at 99% confidence level. Specifically, the predicted probability that the female patients smile, on average, is higher than that of male patients with the other factors constant. As the result of the regression, we obtained estimated propensity scores between 0.4887 and 0.5606 with a mean value of 0.5339 and a standard deviation of 0.0308 according to table 11.

[Insert Table 10 Here]

[Insert Table 11 Here]

In table 12, using the nearest neighbor matching method, we matched each observation in the treated group with the corresponding one in the control group with the most similar estimated propensity score. The result suggests that the positive effect of "smile" on the percentage of active funders (NOAF, %) and the percentage of active funders with initials (NOIFU, %) is significant at 95% confidence level. On average, within subclasses where campaigns are homogeneous, campaigns with patients smiling have 2.7% more active funders than the rest if the other characteristics are identical. In other words, if a patient smiled, the same campaign could attract 2.7% more active funders.

[Insert Table 12 Here]

The evidence supports hypothesis 7: a larger fraction of total funders would be composed of active funders if patients smiled in their profile pictures. The possible explanation can be that, on HCCF, smile is a signal for funders that patients are more likely to be kind and honest (Thornton, 1943), which would strengthen their belief that their donation can change the patients' lives (Kuppuswamy & Bayus, 2017) and they have maximized the value of their donation. In other words, the social return from the success of campaigns

[8] Stata is a complete, integrated statistics package for data analysis, data management, and graphics.

(Moore et al., 2012) encourages active funders to donate faster. Similar to the percentage of active funders in general, the percentage of active funders with initials would be 2.1% higher if patients smiled, at the confidence level of 95%, which means that "smile" could attract more extroverted active contributors. The active funders being involved in campaigns on Watsi are more likely to continue donating to campaigns and advertising for Watsi and HCCF on their social media. Thus, in the long run, the "smile" would have a positive effect on the funding speed. However, we did not find significant evidence to support the same hypothesis for the active funders with pictures and active anonymous funders. These results might indicate that unlike active funders with initials who have a similar perception of patients' smiling faces, active funders with pictures and active anonymous funders may hold different opinions towards patients' smiling faces from each other.

We also deployed propensity score matching with the treatment as "life-threatening words". There is no significant average treatment effect, which means we cannot reject the null hypothesis of hypothesis 8 at 90% confidence level. The reason we did not find sufficient evidence to support hypothesis 8 might be that quite a few active funders do not read the descriptions when they execute their donation. Another possibility could be that since we determined the life-threatening words by reading 500 campaign descriptions which were randomly selected, there might remain other life-threatening keywords that trigger the funders' feeling of urgency but are not covered by our measure.

6. Limitations and Avenue for Further Research

Although we detected several potential factors that can affect the funding speed, there are some limitations with this study. First of all, if funders' profiles can be associated with their social media activities, a deeper investigation on the donating incentive is possible to conduct. In addition, the information cascade among individual investors was found to play a crucial role for the campaign success in equity crowdfunding (Vismara, 2016), but there has not yet been any research discussing the information cascade in HCCF. Involving that factor in this study we would enhance our comprehension of funders' motivation. From the empirical study perspective, we might need to record the time point when funders donated and amount of the donation from each funder, which will enable us to study the immediate reaction of funders on the previous funders' donation behavior.

Life-threatening words are not shown significantly influential in this study, but the results may be biased because of the rules selecting life-threatening words. In future, if the researchers are able to use more advanced tools to detect the life-threatening keywords more accurately, it may turn out that life-threatening words actually impact the funding speed.

Finally, what we also noticed is that Watsi, as a non-profit organization, is improving: they automated emails to notify universal funders about patients' treatment outcomes, added pictures and texts on the website to explain the donating process in details, and even built a digital application to provide community-based health coverage in local communities along with HCCF. All those positive changes could raise awareness for Watsi and make a significant contribution to the goal of universal healthcare coverage. If the future studies could focus on these platform-level changes and track the campaign funding speed over a longer period of time, they would be able to provide strategic recommendations to Watsi.

7. Conclusion

Crowdfunding has arisen as an alternative method of financing entrepreneurship, arts and, music. Likewise, it has become a method of collecting funds for medical treatment. Unlike most developed countries, many developing countries do not have the universal healthcare coverage. The overseas crowdfunding diminishes geographic limitations by invoking the crowd to fill the funding gap.

We study the mechanism of Watsi and search for the factors that influence the funding speed. Holidays play a role in determining funding speed: if the campaigns are posted before, during or after an important American holiday, they need significantly less time to complete with all of the other factors constant. Therefore, Watsi could take advantage of this feature to optimize the mechanism by posting more campaigns on Watsi when it is near a holiday. Not only funders would use internet more frequently during the holidays, but also they would feel more satisfied to donate on healthcare crowdfunding platform during those time periods. Furthermore, if the patients are from the poorer countries, they collect the treatment funds faster than the ones from more developed countries if they are similar in terms of the other factors.

Regarding the funders' distribution, three types of funders are linked with a higher speed of funding: active funders with pictures, active funders with initials and universal funders. There are several implications that Watsi can incorporate in its operation. First of all, as signaling effect is reflected, Watsi might like to distribute more of the passive funders' donation to the campaigns when those campaigns are in their early stage. Secondly, although Watsi could not change the patients' personality, its broader presence on the social media would even motivate the introverted funders to share the campaigns or Watsi-related news on social media, which in turns speeds up the campaigns. The patients' smiles can positively impact the funding speed in the long run. This is associated with more active funders and particularly active funders with initials: if the patient smiled, he/she would get a larger percentage of active funders and especially a larger percentage of active funders with initials.

We hope that this study contributes to illustrating the different ways that each factor affects the speed of HCCF. Finally, we wish for our recommendations to be seen as insightful by the medical community, so that patients may benefit from the possible efficiency improvements that follow from our findings.

References

Agrawal, A. K., Catalini, C., & Goldfarb, A. (2011). The geography of crowdfunding (No. w16820). National bureau of economic research. (http://www.nber.org/papers/w16820)

Agrawal, A. K., Catalini, C., & Goldfarb, A. (2015). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy, 24*(2), 253-274.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955-980.

Allison, T. H., Davis, B. C., Short, J. C., & Webb, J. W. (2015). Crowdfunding in a prosocial microlending environment: Examining the role of intrinsic versus extrinsic cues. *Entrepreneurship Theory and Practice, 39*(1), 53-73.

Amichai-Hamburger, Y., & Vinitzky, G. (2010). Social network use and personality. *Computers in Human Behavior*, *26*(6), 1289-1295.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. *Journal of Business Venturing, 29*(5), 585-609.

Brabham, D. C. (2008). Crowdsourcing as a model for problem solving: An introduction and cases. *Convergence, 14*(1), 75-90.

Bruton, G., Khavul, S., Siegel, D., & Wright, M. (2015). New financial alternatives in seeding entrepreneurship: Microfinance, crowdfunding, and peer-to-peer innovations. *Entrepreneurship Theory and Practice, 39*(1), 9-26.

Burtch, G., & Chan, J. (2014). Reducing medical bankruptcy through crowdfunding: Evidence from GiveForward. (https://aisel.aisnet.org/icis2014/proceedings/ISHealthcare/35/)

Carrin, G., Waelkens, M. P., & Criel, B. (2005). Community-based health insurance in developing countries: a study of its contribution to the performance of health financing systems. *Tropical medicine & international health*, *10*(8), 799-811.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31-72.

Chatterjee, S., & Price, B. (1991). *Regression diagnostics*. New York, NY.

Colombo, M. G., Franzoni, C., & Rossi-Lamastra, C. (2015). Internal social capital and the attraction of early contributions in crowdfunding. *Entrepreneurship Theory and Practice, 39*(1), 75-100.

Cox, D. R., & Oakes, D. (1984). *Analysis of survival data,* CRC Press.

Cumming, D. J., Hornuf, L., Karami, M., & Schweizer, D. (2016). Disentangling crowdfunding from fraudfunding. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2828919)

Deng, Y. (1997). Mortgage termination: An empirical hazard model with a stochastic term structure. *The Journal of Real Estate Finance and Economics, 14*(3), 309-331.

Eisenberg, N., Miller, P. A., Schaller, M., Fabes, R. A., Fultz, J., Shell, R., & Shea, C. L. (1989). The role of sympathy and altruistic personality traits in helping: A reexamination. *Journal of Personality*, *57*(1), 41-67.

Geobey, S., Westley, F. R., & Weber, O. (2012). Enabling social innovation through developmental social finance. *Journal of Social Entrepreneurship, 3*(2), 151-165.

Gerber, E. M., Hui, J. S., & Kuo, P. Y. (2012). Crowdfunding: Why people are motivated to post and fund projects on crowdfunding platforms. ACM Conference on Computer Supported Cooperative Work and Social Computing. ⟨http://www.juliehui.org/wpcontent/uploads/2013/04/CSCW_Crowdfunding_Final.pdf⟩

Golbeck, J., Robles, C., & Turner, K. (2011). Predicting personality with social media. Paper presented at the *CHI'11 Extended Abstracts on Human Factors in Computing Systems,* (pp. 253-262). ACM.

Greenberg, M. D., Pardo, B., Hariharan, K., & Gerber, E. (2013). Crowdfunding support tools: Predicting success & failure. Paper presented at the *CHI'13 Extended Abstracts on Human Factors in Computing Systems,* (pp. 1815-1820). ACM.

Günther, C., Johan, S., & Schweizer, D. (2018). Is the crowd sensitive to distance?—How investment decisions differ by investor type. *Small Business Economics*, 50(2), 289-305.

Jalan, J., & Ravallion, M. (2003). Estimating the benefit incidence of an antipoverty program by propensity-score matching. *Journal of Business & Economic Statistics, 21*(1), 19-30.

Jones, E. E., & Davis, K. E. (1965). From acts to dispositions the attribution process in person perception. In *Advances in experimental social psychology* (Vol. 2, pp. 219-266). Academic Press.

Kasser, T., & Sheldon, K. M. (2002). What makes for a merry Christmas? *Journal of Happiness Studies, 3*(4), 313-329.

Kleemann, F., Voß, G. G., & Rieder, K. (2008). Un(der) paid innovators: The commercial utilization of consumer work through crowdsourcing. *Science, Technology & Innovation Studies, 4*(1), 5-26.

Koch, J., & Siering, M. (2015). Crowdfunding success factors: The characteristics of successfully funded projects on crowdfunding platforms. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2808424)

Kuppuswamy, V., & Bayus, B. L. (2018). Crowdfunding creative ideas: The dynamics of project backers. In *The Economics of Crowdfunding* (pp. 151-182). Palgrave Macmillan, Cham.

Kuppuswamy, V., & Bayus, B. L. (2017). Does my contribution to your crowdfunding project matter? *Journal of Business Venturing, 32*(1), 72-89.

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the cox proportional hazards model to bank failure. *Journal of Banking & Finance, 10*(4), 511-531.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review, 94*(2), 208-211.

Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *The Review of Economics and Statistics, 84*(2), 205-220.

Lee, Y. K., & Chang, C. T. (2007). Who gives what to charity? Characteristics affecting donation behavior. *Social Behavior and Personality: An International Journal*, *35*(9), 1173-1180.

List, J. A., Millimet, D. L., Fredriksson, P. G., & McHone, W. W. (2003). Effects of environmental regulations on manufacturing plant births: Evidence from a propensity score matching estimator. *The Review of Economics and Statistics, 85*(4), 944-952. Ly, P., & Mason, G. (2012). Competition between microfinance NGOs: evidence from Kiva. *World Development*, *40*(3), 643-655.

Mitra, T., & Gilbert, E. (2014). The language that gets people to give: Phrases that predict success on kickstarter. Paper presented at the *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing,* (pp. 49-61). ACM.

Moisseyev, A. (2013). Effect of social media on crowdfunding project results. (https://digitalcommons.unl.edu/businessdiss/39/)

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29*(1), 1-16.

Moore, M., Westley, F. R., & Brodhead, T. (2012). Social finance intermediaries and social innovation. *Journal of Social Entrepreneurship, 3*(2), 184-205.

Palmer, M. T., & Simmons, K. B. (1995). Communicating intentions through nonverbal behaviors conscious and nonconscious encoding of liking. *Human Communication Research, 22*(1), 128-160.

Parhankangas, A., & Renko, M. (2017). Linguistic style and crowdfunding success among social and commercial entrepreneurs. *Journal of Business Venturing, 32*(2), 215-236.

Pelled, A., Zilberstein, T., Tsirulnikov, A., Pick, E., Patkin, Y., & Tal-Or, N. (2017). Textual primacy online: Impression formation based on textual and visual cues in facebook profiles. *American Behavioral Scientist, 61*(7), 672-687.

Peters, D. H., Garg, A., Bloom, G., Walker, D. G., Brieger, W. R., & Hafizur Rahman, M. (2008). Poverty and access to health care in developing countries. *Annals of the New York Academy of Sciences, 1136*(1), 161-171.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41-55.

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in human behavior*, *25*(2), 578-586.

Schweizer, D., & Zhou, T. (2017). Do principles pay in real estate crowdfunding? *Journal of Portfolio Management*, 2017, *43*(6), 120-137.

Schwienbacher, A., & Larralde, B. (2010). Crowdfunding of small entrepreneurial ventures. Handbook of entrepreneurial finance, Oxford University Press, Forthcoming. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1699183)

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business, 74*(1), 101-124.

Small, D. A., Loewenstein, G., & Slovic, P. (2007). Sympathy and callousness: The impact of deliberative thought on donations to identifiable and statistical victims. *Organizational Behavior and Human Decision Processes*, *102*(2), 143-153.

Stevenson, M., & EpiCentre, I. V. A. B. S. (2009). An introduction to survival analysis. *EpiCentre, IVABS, Massey University*.

(http://www.biecek.pl/statystykaMedyczna/Stevenson_survival_analysis_195.721.pdf)

Sy, J. P., & Taylor, J. M. (2000). Estimation in a cox proportional hazards cure model. *Biometrics, 56*(1), 227-236.

Thornton, G. R. (1943). The effect upon judgments of personality traits of varying a single factor in a photograph. *Journal of Social Psychology*, *18*(1), 127-148.

Vismara, S. (2016), Information Cascades Among Investors in Equity Crowdfunding. *Entrepreneurship Theory and Practice*. (http://onlinelibrary.wiley.com/doi/10.1111/etap.12261/full)

Zanutto, E. L. (2006). A comparison of propensity score and linear regression analysis of complex survey data. *Journal of Data Science, 4*(1), 67-91.

Tables and Figures

Tables

Table 1: Variable Description

This table presents the data sources and a brief description of the variables used in this study.

VAR	Source	Description
TIME	Watsi Dataset	Time for finishing a specific campaign (day).
CTREAT	Watsi Dataset	Cost of treatment (thousand $).
AGE	Watsi Dataset	Patients' age: we extracted the patients' age from campaign descriptions.
PAGE	Watsi Dataset	Patients' age category: we divide the patients to four groups according to their age: baby (<1 year old), child (>=1 but <18), adult (>=18 but <60) and senior (>=60). There are three dummy variables and adult is the baseline group.
GDER	Watsi Dataset	Gender. If a patient is female, GDER is 1; otherwise, it is 0.
CNTRY	Watsi Dataset	The home country of patients. Given that Watsi has patients from 24 different countries, We created 23 dummies to control for the effect of country differences.
FBDAY	Watsi Dataset	Whether posted on the first business day: if a campaign was posted on the first business day of the month, FBDAY is 1; otherwise, it is 0.
LFUF	Watsi Dataset	Whether the last funder is universal funder. if the last funder of the campaign is a universal funder, LFUF is 1; otherwise, it is 0.
GDPP	World Bank	GDP per capita (US $).
GDPPR	World Bank	GDP per capita rank: if a patient's country is among the poorer half of the countries, the rank equals to 1; otherwise, it is 0.
PAHD	Watsi Dataset	Whether posted before, during or after a holiday: if the campaign was posted between the 7 days before a holiday and 7 days after the holiday, this dummy equals to 1; otherwise, it equals to 0. The holidays in this study include Christmas, Easter, Thanksgiving and New Year's Day from 2012 to 2016.
NOTF	Watsi Website	Number of total funders. We crawl the funder-related data from Watsi website.

NOUF	Watsi Website	Number of universal funders: universal funders refer the funders who contribute the money to Watsi platform instead of a specific patient.
NOAF	Watsi Website	Number of active funders: funders who make the donation decision by themselves (different from universal funders)
NOIF	Watsi Website	Number of initial funders: funders who disclose their initials when they donate to campaigns.
NOPF	Watsi Website	Number of picture funders: funders who disclose their pictures when they donate to campaigns.
NOIFU	Watsi Website	Number of initial funders without UF; or number of active funders with initials.
NOPFU	Watsi Website	Number of picture funders without UF; or number of active funders with pictures.
NOAFU	Watsi Website	Number of anonymous funders without UF; or number of active anonymous funders.
LFTW	Watsi Dataset	Whether there is at least one life-threatening word in the campaign description. By reading 500 campaign which were selected randomly, we summarized seven sets of the life-threatening words, including “die”/ “death”, “killer”/ “kill”, “cancer”/ “cancerous”, “life-threatening”/ “life threatening”, “survive”, “loss”/ “lose” and “disability”/ “immobility”.
SMILE	Watsi Dataset	Using Microsoft facial expression API, we distinguished whether the patient smiles by coding. This variable is 1 if the coding suggests that a patient is smiling in the picture; otherwise, it is 0.

Table 2: Descriptive Statistics of Numerical Variables

We report in this table the descriptive statistics for the numerical variables. The median of time to finish a campaign is 1.92 days, meaning that over half of the campaigns finish within 2 days. The maximum cost of the treatment (CTREAT) is $3,000; while the average treatment funding sought by patients is only $500. 50% of the campaigns have less than 5 funders (NOTF). With regards to funders' characteristics, on average, a campaign has 3.67 universal funders (NOUF), 4.54 funders with name initials (NOIF) (2.23 or 49% being active funders), and 1.81 funders with profile pictures (NOPF) (0.71 or 39% being active funders). The lowest GDP per capita among the countries in this study is only $286 and 50% of countries have GDP per capita less than $1,095 which is only 10% of the world average.

VAR	Min	Max	Mean	P25	Median	P75	Std	Skew	Kurt
TIME	0.00	68.25	3.35	0.39	1.92	5.09	4.33	3.93	37.92
CTREAT	0.07	3.00	0.63	0.23	0.50	0.98	0.46	0.76	2.39
NOTF	1.00	92.00	9.29	2	5	12	10.26	2.03	8.15
NOUF	0.00	54.00	3.67	0	1	3	6.61	2.95	12.53
NOIF	0.00	42.00	4.54	1	2	6	5.71	2.19	8.71
NOPF	0.00	22.00	1.81	0	1	2	2.63	2.63	11.91
NOIFU	0.00	28.00	2.23	0	1	3	2.68	2.23	11.22
NOPFU	0.0	11.00	0.71	0	0	1	1.08	2.27	10.46
LFTW	0.00	13.00	0.35	0	0	0	0.95	4.97	41.42
GDPP	286.00	12712.43	1400.64	909.33	1094.58	1261.09	1039.69	3.18	19.97

Table 3: Frequency of Dummy Variables

We report in this table the descriptive statistics for the dummy variables. 29% of the patients had a universal funder as their last funder (LFUF). In addition, our coding results suggest that 53% of the patients smile (SMILE) in the campaign pictures; and 20% of the patients have at least one life-threatening word (LFTW) in their campaign description. Lastly, 39% of the patients live in the countries with a lower-than-average GDP per capita among the 24 countries in our sample.

VAR	NO	Percent	YES	Percent
FBDAY	3323	71%	1354	29%
LFUF	3990	85%	687	15%
PAHD	3541	76%	1136	24%
SMILE	2180	47%	2497	53%
LFTW	3731	80%	946	20%
GDPPR	2857	61%	1820	39%

Table 4: Correlation Matrix

We report in this table the Pearson/Spearman correlation coefficients between each pair of potential success factors.

VAR		1	2	3	4	5	6	7	8	9	10	11	12	13	14
CTREAT	1	1													
PAGE	2	-0.163***	1												
SMILE	3	-0.277***	-0.009	1											
LFTW	4	0.102***	-0.134***	-0.052***	1										
CNTRY	5	0.306***	-0.188***	-0.158***	0.051***	1									
GDPP	6	-0.253***	0.186***	0.095***	-0.194***	0.0236	1								
FBDAY	7	0.120***	-0.002	-0.020	0.024	0.065***	-0.069***	1							
LFUF	8	0.063***	0.014	-0.038***	-0.003	0.037**	-0.040***	0.201***	1						
PAHD	9	-0.050***	0.031**	0.022	-0.020	-0.001	0.054***	-0.048***	-0.033**	1					
NOUF	10	0.140***	-0.017	-0.057***	0.012	0.070***	-0.081***	0.457***	0.649***	-0.027	1				
NOIF	11	0.014	0.024	-0.002	-0.008	0.002	0.008	0.221***	0.026	0.063***	0.129***	1			
NOPF	12	-0.067***	0.051***	0.003	-0.000	-0.012	0.041***	0.097***	0.0028	0.051***	0.057***	-0.356***	1		
NOIFU	13	-0.081***	0.045***	0.028	-0.016	-0.023	0.067***	-0.213***	-0.331***	0.056***	-0.494***	0.636***	-0.318***	1	
NOPFU	14	-0.111***	0.053***	0.032**	-0.009	-0.039***	0.057***	-0.091***	-0.192***	0.021	-0.290***	-0.354***	0.786***	-0.191***	1

*** Significant At 99% Confidence Level
** Significant At 95% Confidence Level
* Significant At 90% Confidence Level

Table 5: Variance Influence Factor of the Independent Variables

We report in this table the variance influence factors (VIF). None of the variables have a VIF over 10 – a threshold widely used in statistic studies. Therefore, multicollinearity was not severe enough for us to drop any of the variables.

VAR	VIF	1/VIF
NOUF (%)	4.66	0.214412
NOIFU (%)	4.64	0.215527
NOPFU (%)	4.22	0.236936
NOPF (%)	3.88	0.257567
NOIF (%)	3.68	0.27159
LFUF	1.79	0.55795
FBDAY	1.46	0.684347
CTREAT	1.29	0.773786
GDPPR	1.17	0.853461
CNTRY	1.17	0.857434
PAGE	1.11	0.904329
SMILE	1.11	0.90465
LFTW	1.06	0.946443
GDER	1.03	0.970864
PAHD	1.03	0.973654
Avg. VIF	2.22	

Table 6: Summary of Regression Results for Models (1), (2), and (3)

We report in this table the effects of the success factors on hazard rate. The factors include time used to complete a campaign (TIME), age categories of patients (PAGE), gender (GDER), whether a campaign is posted on the first business day of a month (FBDAY), whether the last funder is universal funder (LFUF), whether a campaign is posted before during or after an American holiday (PAHD) and GDP per capita group of patients' home countries (GDPPR). In model (2), if a campaign is posted on Watsi before, during or after one of the four important holidays (PADH), namely Christmas, New Year's Day, Easter, or Thanksgiving, the campaign wins a hazard rate which is 37% higher than the campaigns posted any other time, with the other variables constant at the confidence level of 99%. In model (3), if two patients have the same profile except for their home countries, the one from a poorer country (among the second half of the 24 countries) (GDPPR) has a higher hazard rate by around 27%, which is significant at the confidence level of 99%.

	(1)		(2)		(3)	
VAR	**Coeff.**	**Hazard Ratio**	**Coeff.**	**Hazard Ratio**	**Coeff.**	**Hazard Ratio**
CTREAT	-0.9134***	0.4012	-0.9236***	0.3971	-0.9178***	0.3994
	(0.00)		(0.00)		(0.00)	
PAGE (Baby)	0.3083***	1.3611	0.3059***	1.3578	0.3047***	1.3562
	(0.00)		(0.00)		(0.00)	
PAGE (Child)	0.3826***	1.4661	0.3821***	1.4654	0.3804***	1.4629
	(0.00)		(0.00)		(0.00)	
PAGE (Senior)	-0.0883*	0.9155	-0.0921*	0.9120	-0.0865*	0.9171
	(0.07)		(0.06)		(0.07)	
GDER	0.0403	1.0411	0.0165	1.0166	0.0199	1.0201
	(0.20)		(0.60)		(0.53)	
FBDAY	0.5113***	1.6675	0.4951***	1.6407	0.4969***	1.6436
	(0.00)		(0.00)		(0.00)	
LFUF	0.4598***	1.5838	0.4604***	1.5847	0.4600***	1.5841
	(0.00)		(0.00)		(0.00)	
PAHD			0.3124***	1.3667	0.3123***	1.3666
			(0.00)		(0.00)	
GDPPR					0.2417***	1.2734
					(0.01)	
Year fixed effect	Yes		Yes		Yes	
Observations	4677		4677		4677	

*** Significant at 99% Confidence Level
** Significant at 95% Confidence Level
* Significant at 90% Confidence Level

Note: Hazard ratio is calculated as the exponent of the coefficient. For example, the coefficient of CTREAT is -0.94726; the hazard ratio is (exp(-0.94726) = 0.3878). It means that increasing treatment cost by $1,000 reduces the hazard rate by a factor of 0.3878, or (1-0.3878) = 61%. Therefore, raising treatment cost is associated with bad prognostic.

Table 7: Summary of Regression Results for Models (4) and (5)

We report in this table the results when involving three additional types of success factors, including each funder's proportion, patients' smiles, and life-threatening words. In model (4), holding the other factors constant, the hazard rate would rise by 683% if a campaign consisted of 1% more universal funders. Similarly, percentage of active funders with pictures (NOPFU, %) and percentage of the active funders with initials (NOIFU, %) are also positively related to the funding speed. However, whether a patient smiles in the profile picture (SMILE) and whether the description of a campaign has at least one life-threatening word (LFTW) are not statistically significant at 90% confidence level.

	(4)		(5)	
VAR	**Coeff.**	**Hazard Ratio**	**Coeff.**	**Hazard Ratio**
CTREAT	-0.9277*** (0.00)	0.3955	-0.9262*** (0.00)	0.3961
PAGE (Baby)	0.3238*** (0.00)	1.3824	0.3298*** (0.00)	1.3907
PAGE (Child)	0.3707*** (0.00)	1.4487	0.3818*** (0.00)	1.4649
PAGE (Senior)	-0.0958** (0.05)	0.9086	-0.0939* (0.05)	0.9104
GDER	0.0169 (0.59)	1.0170	0.0157 (0.62)	1.0158
FBDAY	0.4237*** (0.00)	1.5276	0.4244*** (0.00)	1.5287
LFUF	0.1548*** (0.00)	1.1674	0.1551*** (0.00)	1.1678
PAHD	0.3588*** (0.00)	1.4316	0.3591*** (0.00)	1.4320
GDPPR	0.2304** (0.01)	1.2591	0.2321** (0.01)	1.2612
NOUF (%)	1.9213*** (0.00)	6.8298	1.9217*** (0.00)	6.8326
NOPF (%)	-1.6109*** (0.00)	0.1997	-1.6118*** (0.00)	0.1995
NOPFU (%)	1.2922*** (0.00)	3.6408	1.2916*** (0.00)	3.6386
NOIF (%)	-1.6187*** (0.00)	0.1982	-1.6173*** (0.00)	0.1984
NOIFU (%)	1.5359*** (0.00)	4.6455	1.5338*** (0.00)	4.6358
SMILE			0.0213 (0.55)	1.0215
LFTW			0.0354 (0.36)	1.0360
Year fixed effect	Yes		Yes	
Observations	4677		4677	

*** Significant at 99% Confidence Level
** Significant at 95% Confidence Level
* Significant at 90% Confidence Level

Table 8: Descriptive Statistics of the Treated and Control Groups

In this table, we report the descriptive statistics of covariates between the treated group and the control group. The average cost of treatment in the treated group is $ 764, which is higher than that in the control group of $ 506. In addition, the GDP per capita of patients' home countries in the treated group, on average, is $1,220, which is lower than that in the control group of $ 1,608. Regarding the gender difference, girls are more likely to smile than boys. In terms of age, the patients in the treated group are 17 years younger than the individuals in the control group, which means that the smiling patients tend to be younger on average.

VAR	Treated Group	Control Group
CTREAT (K $)	0.7639	0.5060
GDPP ($)	1220	1608
GDER	0.6528	0.5931
AGE	17.1416	35.3490
FBDAY	0.1546	0.1402
LFUF	0.3078	0.2735
PAHD	0.2330	0.2515
LFTW	0.2248	0.1826

Table 9: Inferior Bound, the Number of Treated and Control Observations for Each Block

We report in this table the inferior bound of blocks and the number of observations in the treated and control groups.

Inferior of block of propensity score	SMILE 0	1	Total
0.4	887	867	1,754
0.5	1,293	1,630	2,923
Total	2,180	2,497	4,677

Table 10: Coefficients of the Probit Regression

In this table, the results of probit regression implies that at least one of the covariates' coefficients is significantly different from 0 at 99% confidence level. Specifically, the predicted probability that the female patients smile, on average, is higher than that of male patients with the other factors constant.

Log likelihood =-3222.178 | Number of obs = 4677 | Prob > chi2 = 0.0001

SMILE	Coef.	Std. Err.	z	P>z
PAGE	-0.007	0.018	-0.420	0.676
GDER	0.159***	0.038	4.180	0.000
_cons	-0.006	0.036	-0.170	0.867

*** Significant at 99% Confidence Level
** Significant at 95% Confidence Level
* Significant at 90% Confidence Level

Table 11: Distribution of Estimated Propensity Score

In this table, we report the distribution of estimated propensity score which are between 0.4887 and 0.5606.

Percentiles	Pscore	Descriptive Stats	
1%	0.4887	Obs	4,677
5%	0.4887	Sum of Weight	4,677
10%	0.4946	Mean	0.5339
25%	0.4946	Std.	0.0308
50%	0.5548	Smallest	0.4887
75%	0.5606	Largest	0.5606
90%	0.5606	Variance	0.0010
95%	0.5606	Skewness	-0.5067
99%	0.5606	Kurtosis	1.2971

Table 12: Result of Nearest Neighbor Matching Method

In this table, we report the results of nearest neighbor matching method for the treatment: smile. Campaigns with patients smiling have 2.7% more active funders than the rest if the other characteristics are identical. In addition, percentage of active funders with initials would be 2.1% higher if patients smiled, at the confidence level of 95%, which means that "smile" could attract more extroverted active contributors.

VAR	n. treat.	n. contr.	Average treatment effect on the treated (ATT)	Std. Err.	T-value
NOAF (%)	2497	1086	0.027**	0.012	2.240
NOPFU (%)	2497	1086	-0.008	0.007	-1.107
NOIFU (%)	2497	1086	0.021**	0.009	2.305
NOAFU (%)	2497	1086	0.013	0.010	1.367

*** Significant at 99% Confidence Level
** Significant at 95% Confidence Level
* Significant at 90% Confidence Level

Figures

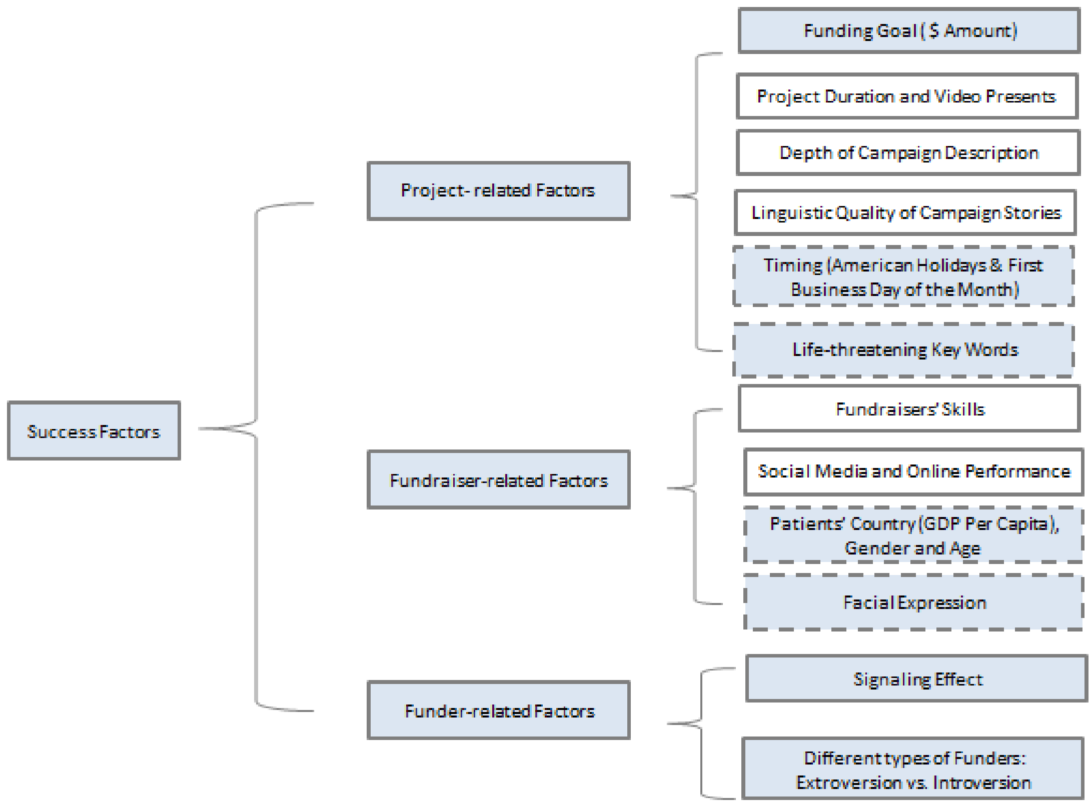

Figure 1: Success Factors from Literatures[9]

[9] The boxes in blue represent the factors that we used in our research, while the white ones represent the other factors that have been discussed in the literature; the boxes with dash border are the factors that we added to the literature, while the boxes with solid border are the factors that have appeared in the literature.

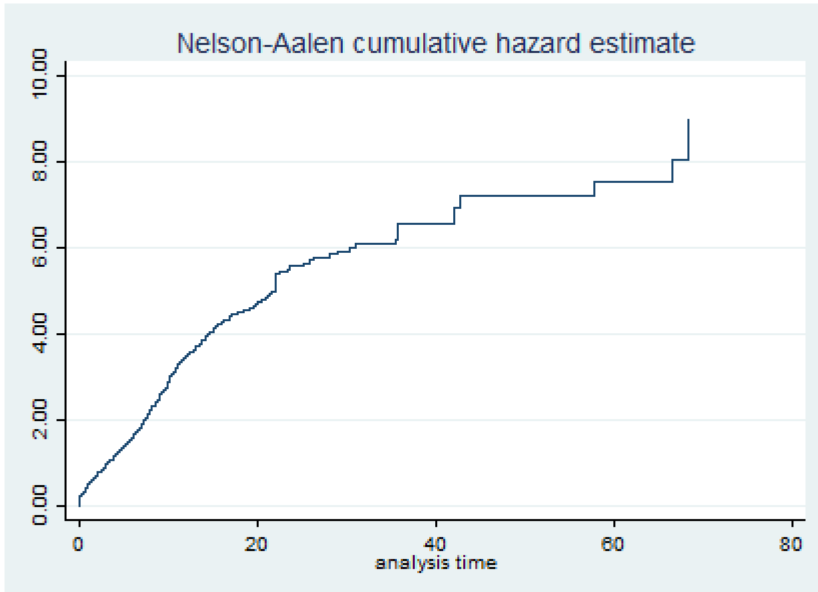

Figure 2: Nelson-Aalen Cumulative Hazard Estimate

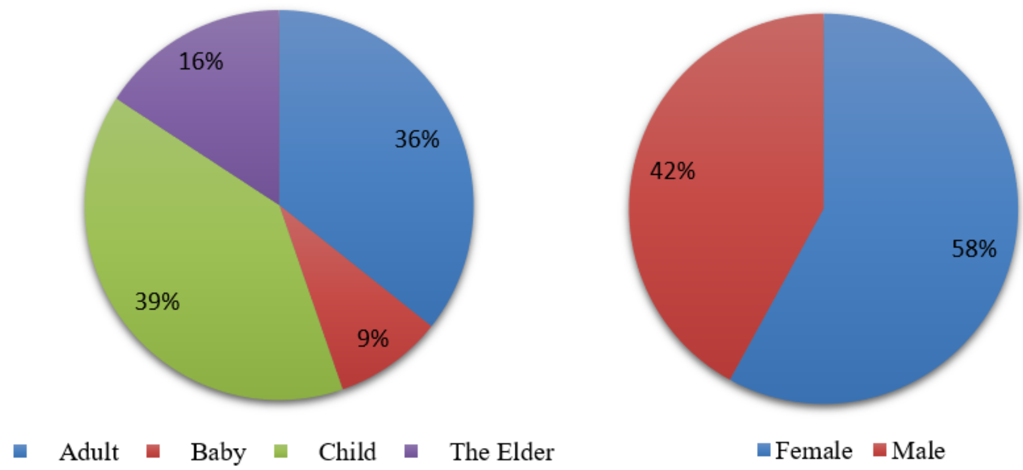

Figure 3: Distribution of Patients

Appendices

Appendix A

Watsi Crowdfunding Home Page: https://watsi.org/crowdfunding

Watsi Crowdfunding Process: Patients seek care from Watsi's medical partners who operate locally. The staff of medical partners have the responsibility to explain the crowdfunding platform and require the permission of patients to share their stories worldwide. If patients agree to start campaigns, medical partners will submit the patients' profiles to Watsi. However, medical partners may begin providing care before patients' profiles are posted or funded. When Watsi posts campaigns online, funders can start donating to the campaigns; 100% of donations go towards patients' treatments. Once treatments are completed, medical partners will submit a post-treatment update on the underlying patients to Watsi, and then Watsi passes the information to funders and transfer the funds to the medical partners to cover the cost of treatments.

A Typical Watsi Campaign: On campaign pages, a profile picture and description of a patient's situation is shown on the left. On the right, funders or potential funders can see the funding goal and progress. The campaign can be shared on Twitter or Facebook directly from Watsi's campaign page. All of the funders are displayed on the bottom-right one after another once they have donated to a campaign. If funders have "Watsi" logos as their icons, they are anonymous funders. Funders, who have their name initials or pictures as their icons, have disclosed their names or uploaded their profile pictures on the website. The small tags on the upper-right corner of funders' icons identify the funders as passive funders (also universal funders) who contribute funds to the platform rather than donate to specific campaigns.

Appendix B

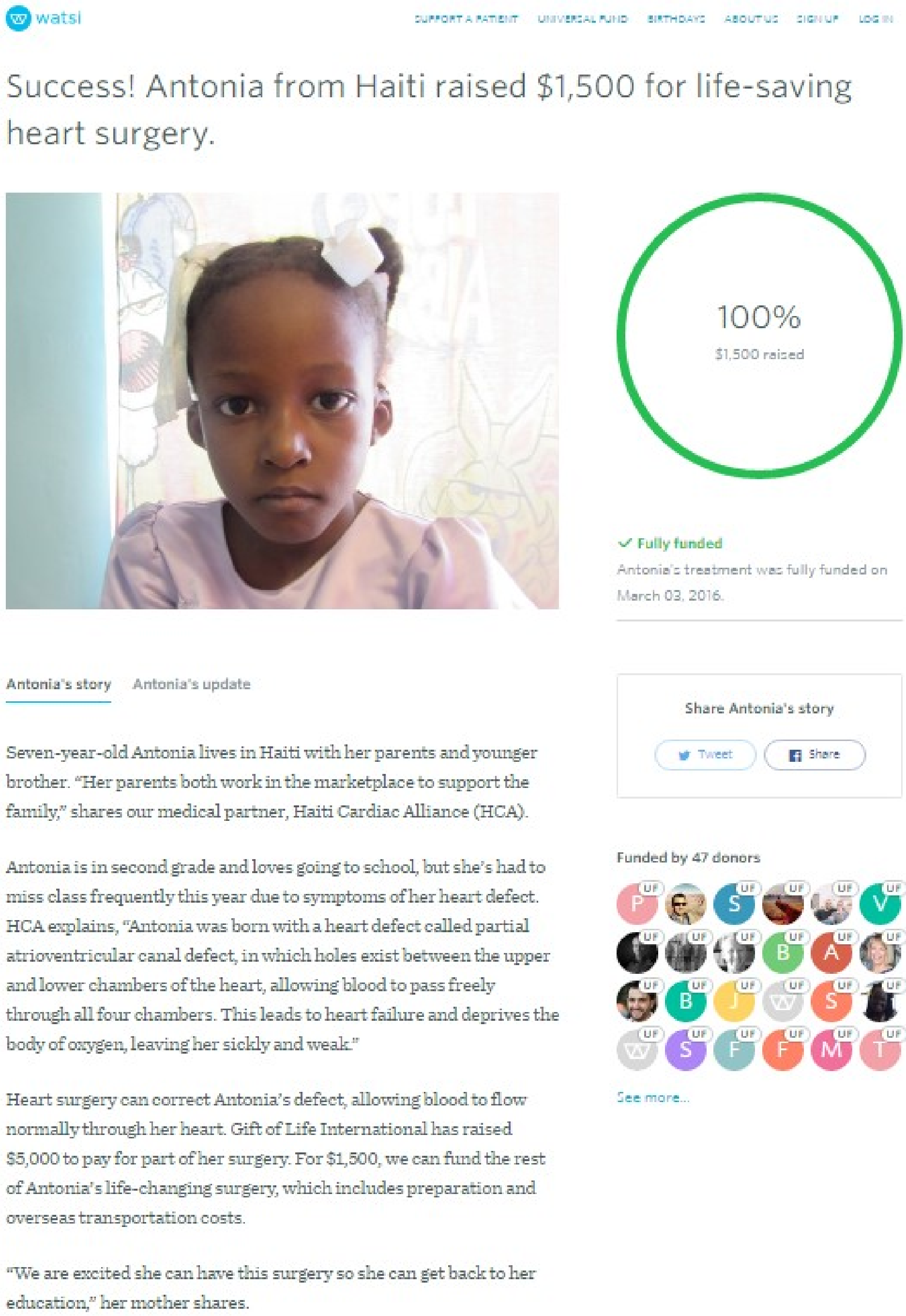

Figure B1: A Typical Watsi Campaign