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# Reward crowdfunding campaigns: Time-to-success analysis

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ABSTRACT

The time-to-success of reward crowdfunding campaigns constitutes a relevant topic that has been neglected in business literature. In this study, we employ parametric and semi-parametric models of survival analysis to identify the determining factors of the duration of success of these campaigns. Based on more than 4200 reward crowdfunding campaigns, our results are robust for controls and reveal that the campaigns that attain success most rapidly are located predominantly in cities with greater income inequality. These are cities that are characterized by lower fundraising targets and receive a larger number of pledges. In addition, our covariates indicate a non-constant influence on time-to-success during the fundraising period.

## 1. Introduction

One of the most emblematic FinTech techniques is that of crowdfunding allowing entrepreneurs of new ventures to fund their efforts by drawing on relatively small contributions from a relatively large number of individuals (pledgers) through internet platforms without the use of standard financial intermediaries (Landström et al., 2019; Mollick, 2014). Crowdfunding financing has grown exponentially in recent years (Scott-Briggs, 2017), especially reward crowdfunding (Chemla & Tinn, 2020; Giudici, Guerini, & Rossi-Lamastra, 2017). A large number of projects that find financing in this market would not have access to any traditional source of financing during the early stage (Hildebrand et al., 2017; Stanko & Henard, 2017).

Understanding the determinants of crowdfunding campaign success over its duration is critical for entrepreneurs and campaign supporters. As campaigns are usually defined as all-or-nothing (a campaign is deemed successful and the pledged money is collected only if the targeted amount is reached in a given limited duration of time), entrepreneurs are required to present campaigns in an attractive fashion as pledgers tend to contribute to campaigns that are perceived as worthy and are expected to succeed. Both entrepreneurs as well as pledgers are interested in a given campaign not only to achieve its target goal, but also to achieve it as quickly as possible (Crosetto & Regner, 2018). As fast as the target goal is reached, the project can start and the rewards can be received sooner. Notwithstanding this aspect, a number of campaigns have met with failure. It is the waste of time for the pledger and the waste of time, effort, and, eventually, money invested for campaign preparation for the entrepreneur, with there being no type of return, not even a non-financial return (Josefy et al., 2017).

In this paper, we provide a replication and extension of previous studies focused on the role of success of crowdfunding campaign determinants by using survival analysis models. Specifically, we aim to identify the factors that impact the time-to-success of reward crowdfunding campaigns and introduce the new factor variables and new methods in the literature. In this sense, besides the factors already analyzed in the literature, we study the new drivers in the new institutional context and provide new results based on the statistical procedures not yet used in crowdfunding literature.

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We argue that the success of reward crowdfunding depends on its perceived viability, social merit, and impact. The pledgers may not only be motivated by self-benefit (the number of rewards received), but also the campaigns' expected social benefits, that is, the types of projects and their ability to reduce inequality and promote social cohesion (Gerber & Hui, 2013). We claim that, in cities with higher inequality, crowdfunding can connect the people in need of funding with the people attempting to contribute to inequality reduction through their pledges, and thus, can positively influence the time-to-success of crowdfunding campaigns. People are satisfied by contributing to projects that make an impact, have social merit, and generate macro-economic implications in terms of income redistribution (Grüner & Siemroth, 2019). In this sense, we argue that the pledgers disregard self-benefit and prefer social benefits, contributing to higher rates for social projects, rather than other project types such as art, and they do so even more intensively in cities with higher income inequalities. We also address the unobserved heterogeneity of the campaigns' quality to ensure the robustness of our results.

From the point of view of entrepreneurs, this knowledge makes it possible to improve the delineation of the fundraising campaign profiles to increase the probability of success and accelerate the rhythm of fundraising. In terms of the current literature and the preeminence of the subject, we have noted that the research on the appropriate models to analyze the time-to-success of crowdfunding campaigns is a subject of equal relevance and little investigation on it (Li et al., 2016), which put together, characterizes the present work as pioneering. In this article, we are particularly interested in gathering new empirical evidence regarding the success of campaigns by assuming an extended definition of success for reward crowdfunding campaigns. This is given that we contemplate not only the fact that the target amount has been achieved (Strausz, 2017), but more importantly, the aspect of time-to-success (Crosetto & Regner, 2018; Li et al., 2016).

We use parametric and semi-parametric models of survival analysis (an umbrella term covering data analysis that describes the expected duration of time until a well-defined event occurs) to examine the determinants of the time-to-success of campaigns. The application of this technique is original in this field, and it generates a better estimation of the model parameters as the survival models incorporate information about the censored and uncensored observations (successful and unsuccessful campaigns) and the duration modeling in the estimation. We use a unique database of 4262 reward crowdfunding campaigns hosted between 2011 and 2016 on the largest crowdfunding platform in Brazil, one of the largest economies of the world (World Bank, 2019). Considering Brazil is a large country with significant socioeconomic asymmetries, reward crowdfunding could prove to be a relevant instrument for reducing inequality (Demir et al., 2016; Demir et al., 2020). The platform we studied raised more than R$ 38 million (1 USD ≈ 3.2 R$ in December 2016 and 5.50 R$ in September 2020) in the period of analysis in an all-or-nothing system, which highlights reward crowdfunding as a relevant form of funding for a variety of entrepreneurial projects.

The dependent variable in the survival analysis consists of two parts: the moment of the event (the campaign's time-to-success) and the status of the event (whether the campaign was a success or failure). The use of censoring in reward crowdfunding campaign survival analysis is a proper strategy to jointly investigate the success and the time-to-success of campaigns. We also carryout controls for the unobserved heterogeneity of the fundraising campaigns and censoring on the 59th and 60th day of the campaigns.

Our results are equally new. They reveal and suggest that the specific attributes of campaigns, such as their location, can influence the time-to-success of reward crowdfunding campaigns. In general, the results show that the campaigns that achieve success more rapidly are characterized by a lower target amount, a larger number of pledges, a smaller number of rewards promised in exchange for pledges, and are predominantly non-art projects located in cities with greater income inequality. In addition, we found out that the covariates adopted in the empirical model influence time-to-success in a non-constant manner during the fundraising period. This has motivated the estimation of parametric models, which ratify the results obtained by the popular Cox proportional hazard (PH) models. Our results are robust to unobserved heterogeneity. This study contributes to crowdfunding literature in three ways. First, to the best of our knowledge, there is still no conclusive evidence regarding the influence of campaign attributes on time-to-success. We assume the campaigns classified as failures could be successful if the active management of the fundraising process was viable during the fundraising period in such a way that it would increase the chances of attaining the target amount. Survival analysis models have advantages over the other binary response models, especially because they rarely allow the time variable to present missing values. In conventional binary analysis, unlike survival analysis, if some of the observations disappear before the end of the observation period, it implies the loss of relevant information about the analyzed event (Efron, 1988; Liu, 2014; Ohno-Machado, 2001).

Second, we believe that the influence of campaign location characteristics is an open question that concerns the concentration of crowdfunding campaigns in certain cities with greater income inequality (Mollick, 2014). We also consider the geographic attributes of the location of reward crowdfunding campaigns. In this respect, we should point out that our results are supported by the data collected of an emerging economy in which social inequalities are explicit and the cost of capital is a limiting factor for the new ventures (Mendes-Da-Silva et al., 2016). Very few research studies on reward crowdfunding have discussed the attributes of the locations in which the campaigns are centered, which may bring out the information regarding the social and economic development of the given region (Florida, 2014). An investigation of the local attributes regarding these campaigns can generate knowledge to promote the effectiveness of crowdfunding campaigns (Giudici, Guerini, & Rossi-Lamastra, 2017). Third, while the literature is essentially characterized by OLS and logit models, we use survival analysis. Given that we also use robust models that violate the main assumption of the most disseminated model of survival analysis, we produce new evidence pertaining to the non-constant impact of the determining factors during the fundraising period. These results may be useful for entrepreneurs, pledgers, platforms, and regulatory agents (Crosetto & Regner, 2018).

If the crowdfunding literature has grown rapidly to the point where the success drivers of campaigns have been reasonably well documented, there is room to consider the possibility of new successful campaign drivers, in addition to the extensions and generalizations based on new evidences arising from new methods and new relevant institutional environments. Our study, even though it uses variables already documented in the crowdfunding literature, contributes to the theoretical and empirical development of this field, especially by promoting the generalization and extension of previous empirical findings. In alignment with Tsang and Kwan (1999, p. 766) and Ethiraj et al. (2016) findings and the principle that science is not built on novelty alone (Babin et al., 2021), we bring out new and revealing evidence that has not yet been explored from an institutional context and explore unique data, new variables, and statistical procedures that are not yet used in the crowdfunding literature. Therefore, we provide additional evidence to help build a cumulative body of knowledge in crowdfunding literature. This study is divided into five sections. Section 2 presents the background and hypothesis of the reward crowdfunding campaign's time-to-success that we tested. Section 3 then presents the methodology we used and the advantages of survival analysis for crowdfunding research. The results of the non-parametric, semi-parametric, and parametric analyses and robustness tests are discussed in Section 4. Finally, the conclusions are presented in Section 5.

## 2. Background and hypotheses

### 2.1. Success of reward crowdfunding campaigns

In accordance with the theoretical fundamentals of crowdfunding (Strausz, 2017), the prediction pertaining to the success of reward crowdfunding campaigns is the key to the development of the crowdfunding industry, given that the prediction of success can assist individuals and organizations not only in their decision-making concerning the allocation of campaign resources, but also in the recommendation of more successful campaigns for individual supporters. According to Strausz (2017), campaign success can be defined as follows: the entrepreneur is first asked to describe the following three elements of his/her campaign on the platform's public webpage: i) a description of the consumer's reward, which is typically the entrepreneur's final product; ii) a pledge level $p$; and iii) a target amount $TA$. After describing these elements, the crowdfunding campaign starts. For a fixed period of time, a consumer (backer or pledger) can pledge an amount $p$ to financially support the campaign. During the campaign, the platform provides accurate information about the aggregate level of the pledges so that a consumer can, in principle, condition his/her decision to pledge on the contributions of previous consumers. After the campaign ends, the platform compares the target amount $TA$ to the sum of pledges $P \equiv n\hat{A}{\cdot}p$, where $n$ is the number of pledging consumers (backers). If the aggregate pledges $P$ fall short of the target level $TA$, the platform declares the crowdfunding campaign a failure.

To the best of our knowledge, the literature (Table 1) has failed to take into consideration the determinants of the time that it takes for a campaign to attain value $P$, which is the main reason why this study is considered relevant, for it contributes to the development and consolidation of the reward crowdfunding theory. There are two particularly relevant aspects in estimating the success of campaigns: the classes of the explanatory variables adopted in the models and the classes of the models employed to estimate success. In terms of the variables, the literature points to various levels of analysis, ranging from the country level (Glazer & Konrad, 1996) to the individual level (Crosetto & Regner, 2018; Hu et al., 2015; Ordanini et al., 2011).

We address the campaign characteristics and the cities in which they are located to test the survival analysis models. According to Lambert and Schwienbacher (2010), a crowdfunding campaign's declared goal can positively influence its success. Meanwhile, Burtch et al. (2013) have found the duration of the fundraising period and the entrepreneur's effort at the beginning of fundraising to have a positive relationship with the success of the campaign. Frydrych et al. (2014), in turn, has argued that the target and structure of rewards are elements that act with greater intensity to raise funds through campaigns. Material compensation (Vukovic et al., 2010) and social recognition (Eiteneyer et al., 2019) play a role in stimulating and increasing the participation of individuals in campaigns (Cholakova & Clarysse, 2015; Steinberg, 2012). The duration of campaigns and the income level of their cities were the predictors of success (Giudici, Guerini, & Rossi-Lamastra, 2017).

As pointed out by Li et al. (2016), the identification of success via conventional binary models may be less robust, given that the models of this class do not distinguish the campaigns that obtained success more rapidly than others, and also treat all the campaigns that were not explicitly successful as failures, no matter how close the total attained was to the target value. In this sense, Lin et al. (2013) have argued that the success attained just on the last day of a campaign may be relevant due to the possibility of friction in this market, and above all due to the moral hazard and asymmetry of information between the agents (Chemla & Tinn, 2020; Crosetto & Regner, 2018; Strausz, 2017).

**Table 1**
Literature Regarding the Success of Reward Crowdfunding Campaigns and their Methods.

| Authorship | Platforms | Method[a] | All-or-nothing[b] |
|---|---|---|---|
| Burtch et al. (2013) | Journalism crowdfunding platform (USA) | 2SLS, OLS and GMM | No |
| Giudici, Guerini, and Rossi-Lamastra (2013) | 11 crowdfunding platforms (Italy) | P | Mixed |
| Crosetto and Regner (2014) | Startnext (Germany) | P | Yes |
| Mollick and Kuppuswamy (2014) | Kickstarter (USA) | OLRR | Yes |
| Mollick (2014) | Kickstarter (USA) | L | Yes |
| Colombo et al. (2015) | Kickstarter (USA) | T and P | Yes |
| Cordova et al. (2015) | Eppela (Italy), Indiegogo and Kickstarter (USA) | P | Mixed |
| Hörisch (2015) | Indiegogo (USA) | L | No |
| Zvilichovsky et al. (2015) | Kickstarter (USA) | L | Yes |
| Koch and Siering (2015) | Kickstarter (USA) | L | Yes |
| Li et al. (2016) | Kickstarter (USA) | SA | Yes |
| Calic and Mosakowski (2016) | Kickstarter (USA) | L and OLS | Yes |
| Hobbs et al. (2016) | Kickstarter (USA) | DA | Yes |
| Shi and Guan (2016) | Jing Dong Crowdfunding Platform (China) | L | Yes |
| Courtney et al. (2017) | Kickstarter (USA) | L and P | Yes |
| Skirnevskiy et al. (2017) | Kickstarter (USA) | L and T | Yes |
| Josefy et al. (2017) | Kickstarter and GoFundMe (USA) | L and RR | Mixed |
| Bi et al. (2017) | zhongchou.com (China) | HMR | No |
| Allison, Davis, Webb, and Short (2017) | Kickstarter (USA) | L | Yes |
| Parhankangas and Renko (2017) | Kickstarter (USA) | L | Yes |
| Giudici, Guerini, and Rossi-Lamastra (2017) | 13 reward-based platforms (Italy) | T | Mixed |
| Chan et al. (2018) | Kickstarter (USA) | L | Yes |
| Clauss et al. (2018) | Visionbakery (Germany) | L | Yes |
| Crosetto and Regner (2018) | Startnext (Germany) | P and PD | Yes |
| De Larrea et al. (2018) | Kickstarter (USA) | HMR | Yes |
| Hörisch (2018) | Ecocrowd (Germany) and Oneplanetcrowd (Europe) | L | Mixed |
| Lagazio and Querci (2018) | Indiegogo (USA) | P | No |
| Oo et al. (2019) | Kickstarter (USA) | L | Yes |
| Da Cruz (2018) | Kickstarter (USA) | P | Yes |
| Zhou et al. (2018) | Kickstarter (USA) | L | Yes |
| Wang et al. (2018) | Dreamore platform (China) | L | Yes |
| Lee and Chiravuri (2019) | Indiegogo (USA) | L | Yes |
| Yang et al. (2019) | Tencent Lejuan crowdfunding platform (China) | OLS | No |
| Yeh et al. (2019) | Zeczec and FlyingV (Taiwanese) Campfire and Makuake (Japan) | L | Yes |
| This study | Catarse (Brazil) | SA | Yes |

Note: 2SLS = two-stage least squares, OLS = ordinary least squares, GMM = generalized method of moments, P = probit, SA = survival analysis, OLRR = ordinal logit with robust errors, L = logit; T = Tobit, DA = discriminant analysis, RR = robust regression, HMR = hierarchical multiple regression, PD = panel data. [a] describes the method employed in the estimation of the campaign's success, and [b] indicates whether the platform considered in the study is of the all-or-nothing type.

### 2.2. Development of the hypotheses

Although the literature documents the relationship between the success of crowdfunding campaigns and a set of determinants, we have not yet found a peer-reviewed study that provides evidence about the impact of success determinants on the time-to-success of campaigns via survival models (Table 1). We provide replication and extensions in three main ways by studying the specific institutional context of Brazil. We use a unique data set and new variables. We use a statistical procedure not yet used in the crowdfunding literature, which allows us to bring new results. Mollick (2014) has argued that the targets of fundraising campaigns are proxies for the quality of the venture's operational characteristics. In this respect, Cordova et al. (2015) have argued that the negative relationship between the fundraising target and the campaign's time-to-success is due to the fact that part of the target amount desired by the entrepreneurs is arbitrary and may not demonstrate the business' effective need for financing. Thus, it is understood that the campaigns that involve a smaller target have a greater probability of obtaining success faster. Basing on this, we formulate $\mathbf{H_1}$ as follows.

$\mathbf{H_1}$. Higher fundraising targets negatively influence the time-to-success of reward crowdfunding campaigns.

In addition to the fundraising target, the number of pledges that contribute to the campaign signal the quality of the project campaign and the credibility of the entrepreneur. Pledgers observe other pledgers' behavior and use this information to generate a dynamic herding behavior (Bretschneider & Leimeister, 2017; Zaggl & Block, 2019). Early success in a campaign may generate positive feedback that reinforces contributions and determines the success of campaigns (Agrawal et al., 2015; Colombo et al., 2015; Josefy et al., 2017). This behavior is expected in the formation of communities as people tend to generate expectations through the participation of other people (Schelling, 1978; van de Rijt et al., 2014). In this manner, through the sense of community and herding behavior, it is expected that the campaigns that receive a greater number of pledges tend to have a greater probability of success. Therefore, we formulate H2 as follows.

$\mathbf{H_2}$. The number of financial pledges received by a campaign positively influences its time-to-success.

On the one hand, material rewards have been indicated as attractive elements for people to make contributions to crowdfunding campaigns (Steinberg, 2012). Participants in reward crowdfunding may wish to participate in financial campaigns to feel that they are part of a community or act for a specific cause (Gerber & Hui, 2013). On the other hand, Cholakova and Clarysse (2015) have argued that a symbolic reward or material reward may not be sufficiently significant to motivate people to enter campaigns, given that people may not trust these ventures and thus, opt not to get involved in any campaign. Rewards may symbolize reduced economic value, and in addition, there is a risk of not receiving them (Scholz, 2015). Thus, rewards alone may not be sufficient to attract contributions (Cholakova & Clarysse, 2015). In any event, the rewards offered in exchange for participation in campaigns can increase a campaign's chances of success, essentially by increasing the number of pledgers (Allison, Davis, Short, & Webb, 2015; Zvilichovsky, Inbar, & Barzilay, 2015). Colombo et al. (2015) share this train of thought and add that rewards may be considered as incentives to attract first-time pledgers. Based on these arguments, we formulate $\mathbf{H_3}$ as follows.

$\mathbf{H_3}$. The number of rewards promised by pledgers promote the time-to-success of campaigns.

According to Mollick (2014), the geographic distribution of campaigns may not be uniform in a given region or country as the grouping of entrepreneurial activities may vary in accordance with local attributes such as the number of inhabitants and economic and social characteristics. This argument suggests that regions do not benefit equally from the financial advantages of crowdfunding (Kim & Hann, 2014). According to Agrawal et al. (2015), the location attributes that can help us understand the concentration pattern of crowdfunding projects are still not well understood, which indicates the need for carrying out research on this subject.

Demir et al. (2020) claim that, although the theory suggests that financial market imperfections (mainly asymmetry of information, market segmentation, and transaction costs) prevent poor people from escaping poverty by limiting their access to formal financial services, FinTechs are seen as the key enablers of financial inclusion (Demir et al., 2020). They provide evidence that financial inclusion is a key channel through which FinTechs reduce income inequality. Grüner and Siemroth (2019) have shown that decentralized individual investments can efficiently allocate capital to innovating firms via crowdfunding. Furthermore, Kimura et al. (2018) have argued that a local disparity in income distribution can encourage pledgers to donate money. According to (2009), economic agglomeration and spatial concentration can influence a city's level of competitiveness, which may be the result of the historic legacy of human capital and the quality of local governance, among other factors. Areas with less income distribution may thus, attract a greater number of crowdfunding ventures (Chen et al., 2010). Furthermore, La Porta and Shleifer (2014) have found states with higher income inequality to be more likely to have higher levels of funding. According to Demir et al. (2020), crowdfunding can induce a reduction in poverty and generate work opportunities. Based on this argument, we propose $\mathbf{H_4}$.

$\mathbf{H_4}$. Campaigns located in cities with a greater concentration of income reach the target amount more quickly.

Crowdfunding can be particularly important for developing countries. According to Stiglitz (2012), governments that seek to promote a more stable economy with a smaller likelihood of a downturn need to be attentive to inequality. Stiglitz (2012) argues that this is because developing countries are more vulnerable to shocks, and believes that efforts should be made to insulate them. Although inequality is relevant to industrialized countries as well (Chambers et al., 2019; Hasanov & Izraeli, 2011), the trade-offs that developing countries face are different. This suggests that particular caution is needed with respect to capital and financial market liberalization. The consideration of income inequality as a motivator for backers to engage in reward crowdfunding campaigns can highlight a research agenda, given the complexity of the background and consequences of income inequality in terms of education, labor market policies, economic growth, and even the population at large (Beal & Astakhova, 2017; Chambers et al., 2019; Hasanov & Izraeli, 2011; Vincens & Stafström, 2015).

With regard to the relationship between inequality (or concentration of income) and the category of campaigns, the literature points out that a large portion of Brazil's population is socially vulnerable (Costa et al., 2018; de Loyola Hummell et al., 2016). In alignment with this, there are arguments in the literature that suggest that individuals may be more sensitive to the crowdfunding campaigns of a social nature, for these can alleviate the problems that are not properly addressed by public officials (Defazio et al., 2021). Despite the fact that there is a willingness to finance projects of an artistic nature in Brazil (Mendes-Da-Silva et al., 2016), this funding does not necessarily come from wealthy individuals. Instead, there are reasons to assume that these individuals prefer to allocate resources to causes that are more oriented toward the solving of social problems, which may be due to altruism or the belief that potential gains can be shared by society (Mollick, 2014).

## 3. Methodology

### 3.1. Data

The data used in this study are unique and come from the largest reward crowdfunding platform operational in Brazil, one of the ten largest economies in the world. The Catarse platform has already raised more than R$ 72 million (1USD ~ 5.50R$ in September 2020) through contributions made by more than 450,000 pledgers in more than 6200 campaigns initiated between 2011 and 2019. The platform adopts the *all-or-nothing* system (Hemer, 2011); therefore, if the target amount established by the entrepreneurs for a given campaign is not attained within the stipulated time frame, the campaign is canceled and the pledgers receive their funds back or get credits to finance other campaigns on the platform (Strausz, 2017).

This study considered all the 4262 campaigns distributed across Brazil's 417 cities during the period 2011–2016, of which 2223 (~52.15%) were successful campaigns and 2039 (~47.84%) were failures. We deal with a wide range of campaign types, ranging from architecture and urbanism (0.8% of the campaigns), science and technology (2%), education and sports (5%), journalism (2.4%), gastronomy (0.2%), environment (1.6%), and mobility and transport (0.6%) to campaigns dedicated toward the financing of art projects (78.5% of the campaigns).

### 3.2. Variables and models

#### 3.2.1. Variables of interest

Based on our review of the literature (Table 1), the variables we investigated as the determinants of time-to-success for reward crowdfunding campaigns are as follows:

. *Success* = a dummy that receives a value of 1 if campaign *i* was successful in attaining the target amount *TA* (Strausz, 2017), and receives a null value if it was not.

.ln*Goal* = the ln of the *TA* value (in R$) desired by campaign *i*. The variable was selected because the target amount can influence campaign success, and also serves as a proxy for the quality of ventures (Giudici, Guerini, & Rossi-Lamastra, 2013; Mollick, 2014).

.ln*Pledges* = the ln of the number of pledgers that financially support a given campaign *i*, until its fundraising period ends. It was selected because this is considered to be an element that attracts other contributions and reduces uncertainty regarding the fundraising process via crowdfunding (Colombo et al., 2015; Josefy et al., 2017).

.ln*Rewards* = the ln of the number of rewards offered during the campaign, it is increased by one unit. According to Frydrych et al. (2014), material rewards can attract more participants to the campaigns.

.*Gini* = coefficient that measures the degree of concentration of income in a given group, i.e., for the city that is hosting campaign *i*. The Gini coefficient receives a value between 0 (an equality situation, i.e., everyone has the same income or there being a perfectly equal distribution of income; in this case, a given city would have 10% of the people with 10% of their income, 20% of the population with 20% of their income, and so on) and 1 (the opposite extreme, i.e., one person holds all of the local wealth or there is absolute inequality) (Krugman, 1992). High inequality would be a level of extreme income inequality. In such a situation, there would be few rich individuals and many poor individuals, implying greater social inequality. However, cities with Gini coefficients closer to zero suggest a more balanced income distribution. Data related to this variable were collected from the most recent census available from the Brazilian Institute of Geography and Statistics (IBGE) (<http://tabnet.datasus.gov.br/cgi/ibge/censo/cnv/ginibr.def>. According to Mollick (2014), the information related to income and spatial location can help us understand the disproportionate concentration of collective ventures and bring out important economic information about the dynamics of crowdfunding.

. *Art* = the dummy variable that receives a value of 1 if campaign *i* is dedicated to financing a project of an artistic nature and a null value if it is not. This variable has been adopted because rewards have been frequently used to finance projects of an artistic nature (Mendes-Da-Silva et al., 2016). The following types of projects are considered art projects: music, cinema and videos, theater, literature, comic books, support for projects in poor communities (folklore or martial arts), art, photography, games, dance, and circuses. The rest were classified as non-art projects (architecture and urbanism, carnivals, science and technology, design, education, sports, events, gastronomy, journalism, environment, mobility and transport, fashion, and social business). Following the procedure adopted by Mollick (2014) as well as the method adopted by the platform we studied, we used a dummy for the campaign categories. Following the recommendations of Carlson and Wu (2012), we adopted a group of control variables that are detailed below.

. *Popold* = percentage of the elderly population in each city with which crowdfunding campaign *i* was developed. This variable was selected because the success of reward crowdfunding may be influenced by demographic variables, especially age (Gamble et al., 2017). In general, entrepreneurs are youth with a limited amount of capital (Gamble et al., 2017). Probably, these entrepreneurs should count on the financial support of people with some financial independence in their financing campaigns. Thus, it seems reasonable to postulate that older people can contribute to projects, especially if they have some family ties with the entrepreneur (Agrawal et al., 2015).

*Illiteracy* represents the percentage of illiteracy in the city hosting the crowdfunding campaign. According to Florida (2002) and Knudsen et al. (2007), human capital should meet the minimum levels of instruction to assure its role in society and in the economy of a given region, which may influence its participation in the crowdfunding campaigns.

The occurrence of a well-defined event, such as a company's bankruptcy, the firing of an executive, or the success of a fundraising campaign, is often a primary outcome in business research. This is essentially a binary outcome (the event has occurred versus it has not occurred). Binary outcome data were analyzed using logistic regressions. However, logistic regression analysis is not appropriate when the research question involves the length of time until the end point occurs (or time-to-event or failure time)—for example, estimating the median of survival times or plotting survival over time after a campaign begins.

In the case of the current study, to develop a better understanding of the subject, instead of time-to-event or failure time, we used time-to-success. Researchers are also particularly interested in knowing if survival times are related to covariates and estimating the size of the effect of a specific covariate. Furthermore, it may initially appear that a research question about the length of a time interval, which is essentially a continuous outcome variable, can be addressed by linear regression or related techniques such as a *t*-test or variance analysis. However, a key distinction between survival times and other continuous data is that the event of interest would occur only in some, not in all the campaigns by the time the fundraising period ends.

When using survival analysis, we provide new evidence by modeling multiple interdependent points in time, instead of modeling a single point. This is because there are a number of problems (which we address via survival analysis) in the latter procedure (Ohno-Machado, 2001). In this regard, we can highlight the following: a single point estimate for a certain time limit may be misleading if its interpretation is extended for longer terms. While an isolated single-point estimate of survival may be useful for certain purposes, it provides no information on whether development seems to be fast or slow for a given campaign. In this sense, a single point estimate cannot illustrate the temporal patterns of crowdfunding campaign development.

Aggregations of serial single-point estimates at pre-specified time intervals can be used to construct a time-oriented, prognostic "survival curve." This estimation is difficult because it involves several time intervals, and data becomes scarcer in some of these intervals (e.g., some cases are lost to follow-up). Therefore, the confidence associated with each single-point estimate may vary significantly. Simple aggregation also does not consider the dependencies of the time-oriented data. Multiple point models are aimed to model survival for a prolonged period of time so that a meaningful survival curve can be generated. In multiple-point models, the outcome estimates of each time point should consider the estimates of other time points so that non-monotonic survival curves are avoided as much as possible. These models generally produce better survival curves than those produced by the aggregation of single-point estimates as they often assume outcome dependency "built in." In these methods, the estimates of survival and hazard functions are produced.

For campaigns that survive (those that have not yet achieved success) until the end of the fundraising period, or which can no longer be followed before the end of the observation period, the entire survival times are unknown. Instead, it is known that the survival time is longer than the observation time. This unique feature of survival data is referred to as right censoring. Ignorance of censored campaigns in the analysis or simple equating of campaigns' observed survival time (follow-up time) with the unobserved total survival time would contribute to the results being biased. Even if there was no censoring in the data set, survival times usually have a heavily skewed distribution, limiting the usefulness of statistical tests that assume a normal data distribution. An analysis of survival data is unique in that the research interest is typically a combination of whether the event has occurred (binary outcome) and when it occurred (continuous outcome). An appropriate analysis of survival data requires specific statistical methods that can deal with censored data.

#### *3.2.2. Survival function and hazard function*

The survivor function is defined as the probability that an entity survives at least up to a certain time $t$, and that it is a non-increasing function. By definition, it has a value of one at time zero and a value of zero at infinity; it is defined as $S(t)$. The determinants of the time to the occurrence of a specific event of interest are common in various fields of research (Bai & Gillen, 2017). Survival analysis intends to obtain a time-dependent function whose value represents the probability of an event occurring after time $t$, or the probability that an event will not occur (survival) until the end of time $t$.

The time-to-success of a campaign is the duration of time between the start of the campaign and its success, i.e., the attainment of the target amount. This survival time is a random continuous variable $T$ with a cumulative distribution function $F(t)$ and probability density function $f(t)$. $F(t)$ is a failure function that provides the probability ($Pr$) that an event will occur before a specific time $t$. Here, $F(t)$ is the probability that a campaign will succeed before $t$. The survival function $S(t)$ is the probability that the duration of a campaign will be greater than or equal to a given time $t$, as in (1).

$$F(t) = Pr(T \leq t) = 1 - Pr(T > t) = 1 - S(t) \tag{1}$$

In other words, the entities where the event does not occur, such as crowdfunding campaigns that attain the target amount during the fundraising period established by the campaign hosting platform, are seen as valuable sources of information with respect to the determinants of the event. One of the most important properties of survival analysis is the capacity to censure observations that are commonly ignored by other methods, such as logit. An analysis of survival provides a group of relevant metrics, which we define below. The most important of these is the survival function denoted in (2) by $S(t|x)$, which provides us with the survival probability at a given point of time, or the proportion of fundraising campaigns that are event-free at time $t$. Since our event of interest is the fact that a crowdfunding campaign has attained its target amount, time is measured by the number of campaign days.

$$S(t|x) = S_0(t)exp\{\beta_0 + \beta X\} \tag{2}$$

where $X$ is the vector of independent variables, $\beta_0$ is the intercept, and $\beta$ is the vector of the coefficients of interest that are required to be estimated. The Kaplan-Meier estimator is a non-parametric statistic for estimating $S(t|x)$ using duration data. In the current study, this estimator measures the fraction of crowdfunding campaigns that have not achieved their target amount at each observed time $t$. The second metric of survival analysis that we have examined is the instantaneous rate of experiencing the event, given that the crowdfunding campaign is event-free at time $t$. This rate was measured using the hazard function denoted by $h(t)$.

The value of $h(t)$ is not a probability. It is rather, a risk indicator of experiencing the event of a campaign attaining the target amount. The larger the values of $h(t)$, the greater the risk that the event will occur later. In addition, $h(t)$ is related to how quickly $S(t)$ diminishes with time. In other words, the hazard function is derived from the survival function over time: $h(t) = \frac{dS(t)}{dt}$. As a result, the hazard function increases over time. To state an example, suppose the two campaigns differ only in their relationship with the binary covariable $x_1$, this would result in (3), which is as follows:

$$S(t|x_1 = 1) = S_0(e^{\beta_1}t) \tag{3}$$

Here, $e^{\beta_1}$ is the acceleration factor of characteristic $x_1$, which signifies that the probability of survival until time $t$ for the campaign with $x_1 = 1$ is equivalent to the probability of 2 until time $e^{\beta_1}t$ for the campaign with $x_1 = 0$. If $\beta_1 < 0$, the factor $e^{\beta_1}$ indicates diminishing (increasing if $\beta_1 > 0$) survival time. For example, if $exp(\beta_1) = 1.05$, then, ceteris paribus, the presence of characteristic $x_1$ implies deacceleration of failure times of 5%, and in this sense, we can say that the success of the campaign is delayed by 5%.

## 4. Results

We discuss the results in five phases. We begin with the discussion of campaigns. Then, we present the non-parametric analysis of the survival function $S(t)$ via Kaplan-Meier curves. Third, we perform a semi-parametric analysis of the hazard function $h(t)$ via the Cox model, and bearing in mind the possibility of a violation of the important assumption of this model, namely Proportional Hazard (PH), we will discuss the results obtained through the parametric analysis of $h(t)$ using accelerated failure time (AFT) via the estimations that assume different distributions, namely Weibull, LogLogístic, and LogNormal. Finally, through a pioneering manner within the reward crowdfunding literature, we use a model dedicated to non-observed heterogeneity. The principal intent for which being the addressal of the empirical challenge arising due to the possibility of problems caused by a bias because of an omitted variable (Keiding et al., 1997; Liu, 2014).

### *4.1. Description of campaigns*

Descriptive information for the 4262 reward crowdfunding campaigns in this study is summarized in Table 2. The campaigns were hosted in 417 cities distributed across five regions of Brazil. The campaigns raised more than R$ 38 million between 2011 and 2016. The target amount of the campaigns was on an average ~ R$ 15 thousand, attracting an average of 96 pledgers.

The average duration of the fundraising time for the campaigns was approximately 49 days, with the time limit established by the platform being 60 days. Almost half of the successful campaigns attained the target amount on the last day of the campaign. In this sense, it is important to evaluate the success of the campaigns via the models that address the issue of censored information. In other words, modeling the time when the campaign remains active on the platform until the target amount is reached, via survival analysis, makes it possible to not only treat successful campaigns as censored information, but also makes it possible to analyze the issue that is particularly relevant and little studied, namely the impact of campaign characteristics on the time-to-

**Table 2**
Descriptive Statistics of the Considered Variables (Successful and Unsuccessful Campaigns).

| | Aggregate (N = 4,262) | Successful (N = 2,223) | Unsuccessful (N = 2,039) | *t*-test |
|---|---|---|---|---|
| Goal | 15,004.52 | 12,386.13 | 17,859.19 | 10.45*** |
| Pledges | 95.98 | 162.34 | 23.63 | −24.49*** |
| Rewards | 8.80 | 9.30 | 8.25 | −7.91*** |
| Duration | 48.89 | 47.23 | 50.68 | 7.95*** |
| Gini | 0.60 | 0.61 | 0.59 | −5.97*** |
| Art | 0.78 | 0.80 | 0.76 | −3.37*** |
| Popold | 8.25 | 8.35 | 8.14 | −3.89*** |
| Illiteracy | 4.50 | 4.15 | 4.89 | 4.85*** |
| Duration % (days) | | | | |
| 1–9 | 1.06 | 1.17 | 0.93 | |
| 10–19 | 3.03 | 3.87 | 2.11 | |
| 20–29 | 5.63 | 6.57 | 4.61 | |
| 30–39 | 10.89 | 12.91 | 8.68 | |
| 40–49 | 19.94 | 21.50 | 18.24 | |
| 50–59 | 5.91 | 6.43 | 5.35 | |
| ≥60 | 53.54 | 47.55 | 60.08 | |

Source: Calculation by the authors. Note: Among the 2,223 successful campaigns, 1,057 (47.5%) achieved success only on day 60, which was the last day of the campaign. The exception is 19 projects (0.85%) in 2015, when the platform adopted a strategy of offering extra time. The maximum duration of these campaigns exceeded the standard time limit of 60 days adopted by the Catarse platform. This occurred due to a policy adopted by the platform to offer extra time for campaigns judged to be close to achieving their target amount. This policy was only implemented in 2015, and affected 30 campaigns, of which 29 had an extension of two days and one had an extension of nine additional days. It should be noted that successful campaigns have, on average, a smaller target amount, more pledgers, more rewards, and are hosted in cities with relative inequality of income distribution (Krugman, 1992). ***$p < 0.01$.

success. Fig. 1 presents the behavior of the total number of pledges to the campaigns per day and the average amount invested (in R$).

This figure suggests that the initial days of fundraising campaigns account for a greater volume of contributions and also receive the highest average amount invested. In failed campaigns, the initial number of contributions per day was 2048. In successful campaigns, the number was about 18 times higher, i.e., 38,203. In addition, the average pledge to the failed campaigns was R$ 75.00, about 13% lesser than the average amount invested in successful campaigns.

We noticed an increase in the number of contributions and the average amount invested on the 59th- and 60th day, i.e., a pattern of increase in the amount of contributions and in the average amount invested. This can be viewed as a possible signal of an attempt to overcome the funding goal in the last days of fundraising. Since the Catarse platform adopts an all-or-nothing financing system, entrepreneurs receive financial resources only if the amount collected is equal to or higher than their project goal. Therefore, we believe that the campaigns' time-to-success should be observed with due attention, especially in terms of the use of statistical censorship. The observations are termed censored when the information about the survival time (success in the current study) is incomplete, and the most often found form is that of right censoring. Suppose crowdfunding campaigns are followed by a study for eight weeks, it is said that a campaign that attains success during the fundraising period is right-censored as the event is observed. Censure is an important issue in survival analysis, and it represents a specific type of absent data. To illustrate this, we use censure of the duration until there is success in four randomly selected crowdfunding campaigns. According to Fig. 2, while the censored campaigns *A* and *B* had success during the established platform duration, the campaigns *C* and *D* were failures.

However, when we observe the performance of campaigns with similar characteristics to these two campaigns in our database, we can see that the other campaigns obtained success with small increases in their durations, such as 7 or 10 days. In this sense, it may not be fair to define the campaigns that achieved substantial fractions of their target amounts (70%, campaign *C*; or 66%, campaign *D*) as failures. This is because, if they had an increase in their duration, they may have been able to achieve success. There are two basic reasons for going beyond the regression to model survival time as a function of a group of predictive variables. First, survival times are generally positive numbers; linear regression may not be the best option, unless these times are first transformed in a manner that removes this restriction (Box-Steffensmeier & Zorn, 2001). Second, and more importantly, common linear regression cannot effectively handle the censure of observations (Efron,

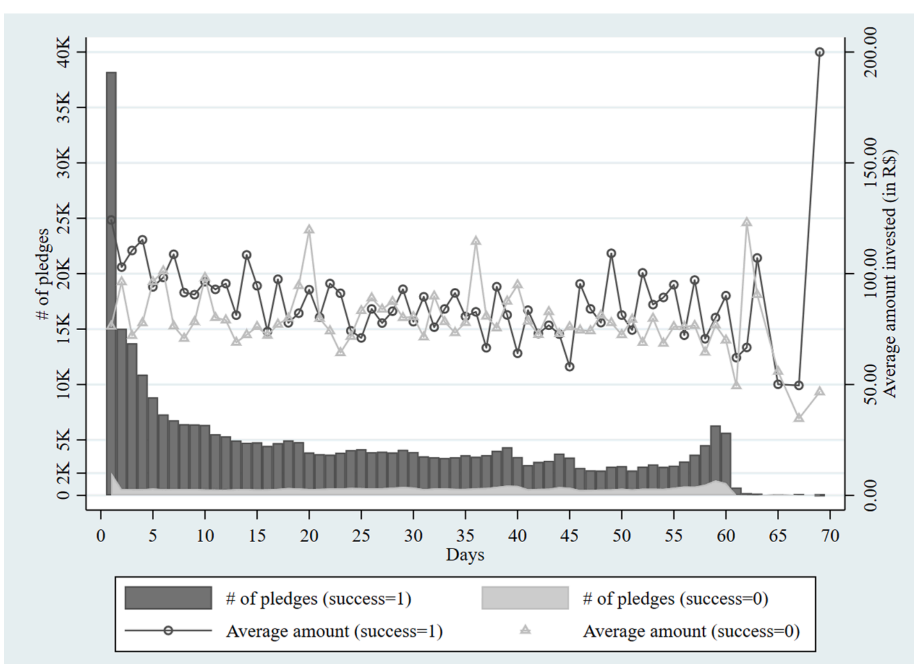


**Fig. 1.** Number of Pledges and Average Amount Invested by Days (Successful and Unsuccessful Campaigns). Source: Calculations by the authors. Note: See note for Table 2.

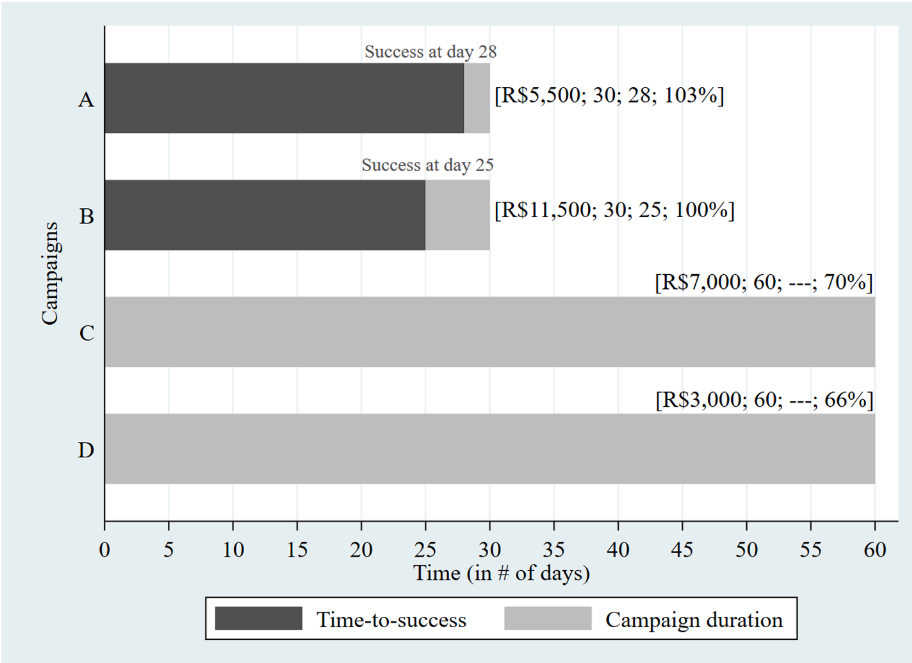


**Fig. 2.** Example of the Implementation of Censure in the Duration of Crowdfunding Campaigns. Source: Calculations by the authors. Note: An example of the four campaigns is randomly selected from the collected data. The horizontal axis represents the duration of the campaign (days). Campaigns *C* and *D* are classified as failures, while campaigns *A* and *B* are successful because they reached the target amount before the end of the campaign. Each campaign is represented in the following format: project identifier ($w$, $x$, $y$, $z$), where $w$ is the campaign's target amount, $x$ is the campaign's duration, $y$ is time-to-success in number of days, and $z$ is the percentage of the target amount received by the final day of the campaign. Even though $w$ and $x$ are available for all campaigns, $y$ is available only for successful campaigns.

1988). Below, we present the survival analysis for time-to-success. Unlike the traditional regression models, survival models incorporate information from censored and uncensored observations correctly while estimating the parameters of important models.

The dependent variable in the survival analysis is composed of two parts: i) the moment of the event (the campaign time-to-success), and ii) the status of the event (a campaign's success or failure), which registers whether the event of interest occurred or not. We believe that the utilization of censure in reward crowdfunding campaign survival analysis can be an interesting strategy to investigate the success of campaigns. In addition, Efron (1988) suggests that the non-utilization of the censure technique may imply biased estimates.

Therefore, survival analysis allows the censure of information regarding the campaigns that achieved success on the last day of the fundraising period established by the reward crowdfunding platform, without having to exclude them from the sample. Owing to this, we use two strategies. The first consists of comparing the results of the survival model for the total campaign with another survival model eliminating the last day (Table 3). That is, the campaigns that obtained success on the last day are considered censored. The stability between the estimated coefficients in the two approaches attests to the occurrence of campaign success on the last day through the use of censure. The second

**Table 3**
Analysis of Campaign Success Factors based on the Cox PH Model.

| | Panel A: Censure 60 (N = 4,262) | | | Panel B: Censure 59 (N = 4,262) | | |
|---|---|---|---|---|---|---|
| | (I) | (II) | (III) | (IV) | (V) | (VI) |
| lnGoal | 0.576*** | 0.576*** | 0.577*** | 0.557*** | 0.557*** | 0.557*** |
| | (0.011) | (0.011) | (0.011) | (0.014) | (0.014) | (0.014) |
| lnPledges | 1.992*** | 1.990*** | 1.989*** | 1.954*** | 1.947*** | 1.944*** |
| | (0.037) | (0.037) | (0.037) | (0.051) | (0.051) | (0.051) |
| lnRewards | 0.783*** | 0.786*** | 0.786*** | 0.698*** | 0.703*** | 0.702*** |
| | (0.045) | (0.045) | (0.045) | (0.053) | (0.053) | (0.054) |
| Gini | 3.321*** | 3.430*** | | 10.72*** | 9.588*** | |
| | (1.385) | (1.362) | | (6.363) | (5.893) | |
| Art | 0.762*** | 0.761*** | | 0.622*** | 0.622*** | |
| | (0.041) | (0.041) | | (0.042) | (0.042) | |
| Gini × Art | | | 3.191*** | | | 8.084*** |
| | | | (1.270) | | | (4.605) |
| Gini × (1-Art) | | | 4.947*** | | | 17.349*** |
| | | | (1.983) | | | (9.913) |
| Popold | Yes | No | No | Yes | No | No |
| Illiteracy | Yes | No | No | Yes | No | No |
| LR $chi^2$ | 1,892.47*** | 1,891.55*** | 1,890.86*** | 1,023.98*** | 1,021.17*** | 1,020.22*** |
| Log-Lik. | −16,607.36 | −16,607.81 | −16,608.16 | −8,953.72 | −8,955.13 | −8,955.60 |
| AIC | 33,228.71 | 33,225.63 | 33,226.32 | 17,921.45 | 17,920.26 | 17,921.21 |
| # of success | 2,223 | 2,223 | 2,223 | 1,166 | 1,166 | 1,166 |

Source: Calculation by the authors. Note: This table presents the hazard ratios (HRs) estimated for the time-to-success of the reward crowdfunding campaigns. The dependent variable was the campaign duration. The estimated models are in the same metric evaluation, which is proportional hazard (PH). Columns I, II, and III refer to the censure of 60 days imposed by the crowdfunding platform, reflecting a situation in which well-informed agents do not act on the final day. Columns IV, V, and VI refer to censure imposed on day 59 of the campaign, designed to not consider campaigns that achieved success on the final day of the fundraising period. All variables are defined in Section 3. *Gini* × *Art*, *Gini* × (1-Art), *Popold* and *Illiteracy* are the controls that were tested in the estimates via Cox regressions. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

strategy consists of adopting survival models with unobserved heterogeneity, the so-called models with frailty (Keiding et al., 1997).

### 4.2. Non-parametric analysis of the campaign survival function

Fig. 3 shows how the survival of the campaigns diminishes over time. As time passes, campaigns obtain success and cease to be part of the survival curve. The concentration of successful campaigns is greater from the start of the 40th day of fundraising period and after the 60th day. According to Panel A, the survival probability rate of campaigns diminishes from 0.87 [$S(40)$ for 60 days]) to 0.37 [$S(60)$ for 60 days]), and according to Panel B, it diminishes from 0.87 [$S(40) = 0.87$ for 59 days] to 0.70 [$S(60) = 0.70$]. This evidence suggests that campaigns tend to obtain success toward the end of this process because their exit from the survival curve is more pronounced when the time approaches the duration established by the platform (Panel A).

However, the strongest effect is perceived when we censure the last day, as in Panel B. In relation to the instantaneous success rate of the campaigns, we may perceive that when we consider 60 days of fundraising (Panel A), the success rate increases from 0.01 [$h(40)$] to 0.08 [$h(60)$]. When we use the 59th day censure (Panel B), the success rate decreases from 0.01 [$h(40)$] to 0.005 [$h(60)$]. The behavior of the instantaneous success rate illustrated in Fig. 3 suggests that when we consider the 60th day censure, the success of the campaigns increases considerably between the 40th and the 60th day of fundraising (Panel A). However, the instant we apply the 59th day censure (Panel B), success suffers a strong decrease, which indicates that the campaigns' late success occurs essentially during the last day of the duration defined by the platform.

### 4.3. Semi-parametric analysis of the campaign hazard function

The most popular model in survival analysis is the Cox proportional hazard regression model, which investigates the relationship between the predictors of time-to-event (or failure time) through the hazard function, $h(t)$. The popularity of the Cox model is essentially due to the fact that it does not require a specific distribution of data, characterizing it as a semi-parametric model (Bai & Gillen, 2017; Kleinbaum & Klein, 2010). In the absence of an expressive group of assumptions to verify, the Cox model assumes a proportional hazard for all the predictor components of the empirical model, a condition without which the estimates may reveal themselves to be invalid. Thus, it is assumed that the predictors have a multiplicative effect on the hazard, and that this effect is constant over time, in accordance with (4):

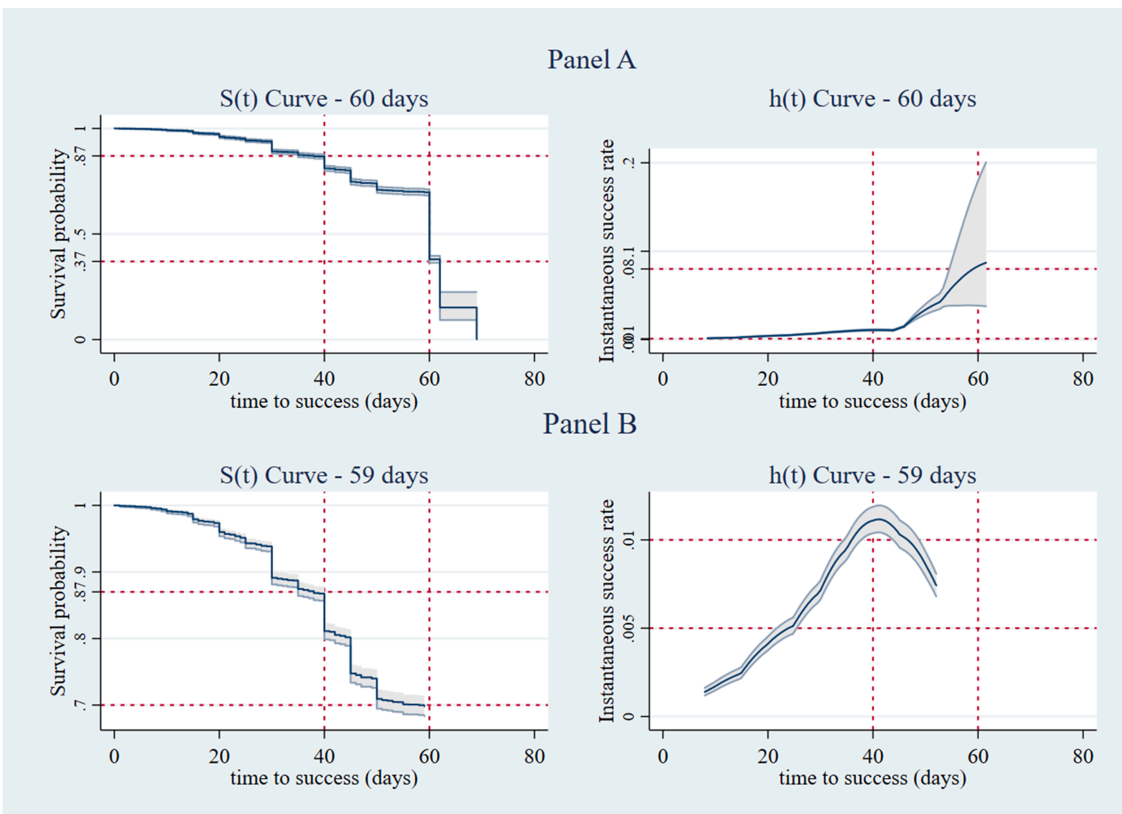


**Fig. 3.** Estimates for Time-to-Success (Kaplan-Meier Survival Estimates, $S(t)$) and the Smoothed Hazard Estimate, $h(t)$) for Campaigns of 60 and 59 days. Source: Calculation by the authors. Note: This figure presents a graphical representation of the survival function $S(t)$ with probabilities estimated by the Kaplan-Meier method including 95% confidence bands, and on the right, curves that describe the instantaneous rate of occurrence of the event over time, namely the hazard function $h(t)$ estimated for the time-to-success of reward crowdfunding projects with fundraising campaigns up to 60 days (Panel A), and up to 59 days (Panel B). Censoring is indicated by vertical marks (at 40 and 60) for Panel A and vertical marks (at 40 and 59) for Panel B. The number of campaigns at risk points (success at different times) is displayed in the graph. The point in Panel A (60 days) on the x-axis, where the horizontal dashed line has a survival probability of 0.87, intersects the curve representing the estimated median survival time (40 days) and 0.37 for median survival time (60 days). On the y-axis, where the vertical dashed line at a smoothed hazard estimate of 0.01, the curve represents the estimated instantaneous success rate (40 days) and 0.08 for the instantaneous success rate (60 days). In Panel B, on the x-axis, where the horizontal dashed line, which has a survival probability of 0.87, intersects the curve represents the estimated median survival time (40 days) and 0.70 the median survival time (60 days), respectively. On the y-axis, the point where the vertical dashed line at a smoothed hazard estimate of 0.01 intersects the curve represents the estimated instantaneous success rate (at 40 days) and 0.005 for the instantaneous success rate (at 60 days). The censuring for the 59 day campaign does not consider the campaigns that achieved success on the last day of the fundraising period. Based on this figure, it is possible to understand that the longer the campaign, the greater the chance of success. Table 2 shows the 40th and 60th days as the highest concentrations of successful campaigns.

$$h(t|x) = h_0(t)exp\left(X_1\beta_1^{PH} + X_2\beta_2^{PH} + \cdots + X_n\beta_n^{PH}\right) \quad (4)$$

where $X_i$s is a set of explanatory variables that shift the hazard function proportionally, $\beta_i^{PH}$s are the parameters to be estimated, and $h_0(t)$ is called the "baseline hazard …the value when all $X_i$s are equal to zero" (Bradburn et al., 2003, p. 432). In the Cox specification, no assumption is made regarding the distribution of $h(t)$. The Cox model was interpreted in terms of hazard ratios (HRs), defined as the ratio of the predicted hazard function. An HR greater than 1 implies that the event is more likely to occur, and an HR less than 1 implies that the event is less likely to occur (or the predictor does not have an effect on the event's hazard).

Note that the hazard function $h(t)$, which in this study represents an approximation of a campaign obtaining success at each instant of time, presents an apparently distinct behavior in the two models (Kaplan-Meier survival estimates, $S(t)$; and the smoothed hazard estimate, $h(t)$). For the model with complete information (the upper right corner of Fig. 3), the hazard increases slowly until approximately the 40th day and accelerates until approximately the 60th day. Meanwhile, for the model that does not consider the successes of the final day (the lower right corner of Fig. 3), we may observe an increase in the success rate (HR) of the campaign until the 40th day; however, the success rate diminishes by the 59th day.

In terms of the possibility that the campaigns that achieve success on the last day have received financial assistance from a well-informed agent, as investigated by Crosetto and Regner (2018), it should be questioned if the role of the covariates for the chances of the project's success is not biased as these projects are considered successful. In this sense, by using the premise of PH, Table 3 presents the hazard ratios estimated by the Cox regressions based on the complete sample, with there being censure of the campaigns that obtained success on the final day.

In all of the models presented in Table 3, our hypotheses were supported. Columns I, II, and III provide details about the campaigns that achieved success on the last day of the period. The hazard ratios estimated for ln*Goal* and ln*Pledges* suggest that the hazard ratio (campaign success) diminishes by 42.4% [i.e., (1–0.576) * 100] with an increase of 172% in the target amount (ln*Goal*), and increases by 99% [i.e., (1.990–1) * 100] with an increase of 172% in the number of pledges (ln*Pledges*). In support of $H_1$ and $H_2$, while we found the campaigns with greater financial targets tending to have lower chances of success (hazard ratio below 1), we found campaigns with more supporters showing greater chances of success (hazard ratio above 1).

This result presents the role of community involvement and herding behavior in generating pledges since the early days of a campaign as the determinants of campaign success, in line with Colombo et al. (2015), Agrawal et al. (2015), and Josefy et al. (2017). In terms of the number of rewards promised in exchange for contributions ($H_3$), the results suggest that the campaigns that promise more rewards in exchange for contributions present lower chances of success. This result contradicts the results obtained by Frydrych et al. (2014), Zvilichovsky et al. (2015), and Colombo et al. (2015); it supports the arguments of Cholakova and Clarysse (2015), who have argued that the non-financial reasons (symbolic or material rewards) are not sufficiently significant to motivate individuals to actively participate in crowdfunding campaigns.

An alternative interpretation of this result is that campaigns offer more rewards when they are trying to compensate for the problems related to the quality of their venture (Vismara, 2018). This line of thinking is defended by Mollick (2014), who has alleged that the campaigns are not in line with reality (elevated targets and rewards) and can end up signaling the businesses' inferior quality, placing the success of the campaigns at risk. In this sense, if material rewards play the role of attracting more participants to campaigns, as pointed out by Frydrych et al. (2014), the effects of rewards and pledgers tend to be confused by the merely descriptive studies. The Cox regression suggests to us (controlled for the number of pledgers) that the number of rewards offered act more as a signal of campaigns dedicated to bad projects, rather than generating incentives. It also signals that the motivation to contribute to the campaigns is not rewards, but rather involvement in the community and altruistic participation.

In accordance with $H_4$, we have verified that the campaigns initiated in cities with greater income inequality tend to have a greater probability of success. This finding supports the idea that crowdfunding can reduce inequality, offer work opportunities, and contribute toward the reduction of inequalities between regions, even in emerging economies (2016). In column III, we separated the *Gini* effects of the campaigns, which were classified as art-related or not. The most notable effects were found for the *Gini* of non-artistic projects. It is expected that the propensity to invest resources in reward crowdfunding is greater if the campaign is dedicated to financing new ventures that have the potential to contribute to disadvantaged regions, given that non-artistic campaigns are more likely to be classified as new venture projects. This argument is based on the assumption that altruism can play a dominant role in the success of campaigns, especially in cities that have a greater income inequality. This finding seems to be connected to the work of Mollick (2014), which reveals a strong preference for non-artistic campaigns on the part of pledgers, namely graphic design, hardware, software, product design, and technology.

The corresponding estimated effects when we exclude the successes obtained on the last day (Censure 59) are all in the same direction, which confirms the hypotheses $H_1$, $H_2$, and $H_4$ and contradicts $H_3$. If the last day of the campaign is effectively influenced by agents with additional information, such as campaign entrepreneurs or platform owners, this strengthens the importance of project characteristics and location to the detriment of the proponent's contact network. The corresponding estimated effects when we exclude the successes on the last day (Censure 59) are not that distinct, except when we observe the inequality of income distribution. This result suggests that the campaigns with elevated fundraising targets ($H_1$) present lower hazard ratios; to put it in other words, the chances of success. In accordance with Mollick (2014) and Giudici, Guerini, and Rossi-Lamastra (2013), pledgers have a certain preference for projects with smaller financial dimensions, which are in alignment with the scope of the venture.

On the other hand, campaigns that receive a larger number of pledges ($H_2$) demonstrate greater HR, and as a result, a greater probability of success. The literature indicates that, the more pledges a campaign has, the greater its chances of success (Naar, 2016). This is because the effort dedicated to the campaign tends to be diluted among a larger number of individual contributions (Naar, 2016). Our results converge with those of Colombo et al. (2015), Agrawal et al. (2015), and Josefy et al. (2017). In terms of the number of rewards promised in exchange for contributions ($H_3$), the results suggest that the campaigns that promise more rewards in exchange for contributions have lower chances of success (HR), with there being a value of about 0.78 for models with Censure 60 and 0.70 for models with Censure 59.

While this contradicts the results obtained by Frydrych et al. (2014), Zvilichovsky et al. (2015), and Colombo et al. (2015), this supports the arguments of Cholakova and Clarysse (2015), who have argued that non-financial motives (symbolic or material rewards) are not sufficiently significant to motivate individuals to participate actively in crowdfunding, and given that they represent relevant economic value, they run the risk of not being delivered (Scholz, 2015). An alternative interpretation of this result is that the campaigns that offer the greatest number of rewards may be signaling that they are trying to compensate for the problems related to the quality of their venture (Vismara, 2018). This line of thinking is argued by Mollick (2014), who has alleged that the campaigns are not in line with reality (elevated targets and rewards). This can end up signaling the inferior quality of businesses, placing the success of the campaigns at risk. In accordance with $H_4$, we verified if the campaigns developed in cities with greater income inequality tend to present greater probabilities of success.

Columns I, II, IV, and V indicate that the campaigns initiated in cities with greater income inequality present greater HR, or in other words, have greater chances of success. This finding supports the idea that crowdfunding can reduce inequality, offer work opportunities, and contribute toward the reduction of inequality among regions, including the emerging economies (2016). Unlike the other variables, the *Gini* appears to have a greater effect on the success of the campaign during the period, as demonstrated by columns IV, V, and VI. The estimates indicate that the artistic $[Gini \times Art]$ and non-artistic campaigns developed in cities with greater income inequality are the most successful. However, most of the marginal effects were registered for non-artistic campaigns. This is to say that, the greater the income concentration in the host city, the greater are the chances of success with non-artistic campaigns in comparison to others. Non-artistic campaigns in cities with great income inequality have a greater probability of success when we control for Censure 59 (a coefficient of 8.1 for artistic campaigns and 17.3 for non-artistic campaigns, model VI in Table 3).

In other words, the campaigns dedicated to non-artistic projects, located in cities with greater income inequality, tend to have greater chances of success in comparison to the other campaigns. This finding highlights the supposition that altruism can play a dominant role in campaign success, particularly in cities where income inequality is greater. This finding seems to be in line with Mollick (2014), who finds a strong preference among pledgers for campaigns related to graphic design, software, product design, and technology. We implemented the Log-rank test (Mantel, 1966; Savage, 1956) to understand if our data presents the equality of survivor function over time, a situation that does not violate the PH assumption on which the Cox model is based. As can be seen from the coefficients presented in Table 4, we reject the hypothesis that the estimated parameters do not vary over time. Thus, helping us understand that the parametric models are more adequate for analyzing the data in this study.

### 4.4. Parametric analysis of the campaign hazard function

Parametric models assume a specific distribution of survival times. They hold advantages such as greater efficiency (or greater power according to Bradburn et al., 2003), which can be particularly useful with smaller samples. The Cox semi-parametric model is seen as a secure and proven method, which does not require a specific distribution of data. Thus, it is the most commonly used model in the analysis of survival data, while depending on the PH assumption.

Campaign characteristics can influence the duration of the fundraising period, and they can also exhibit non-constant effects over time, violating the important assumption of the PH model, as shown in Table 4. A variety of parametric techniques can model survival times when the PH assumption is violated. However, it is a challenge for researchers to determine the most appropriate data distribution, and parametric models have the disadvantage of providing misleading inferences if the distributive assumptions are not met (Hosmer et al., 2008). In the case of the violation of the PH assumption, the use of parametric survival models is suggested, which assumes a particular distribution of survival. There are three main forms: i) the parametric proportional hazard model, which takes the form of the Cox model but assumes a parametric form for the baseline hazard; ii) the additive hazard model, in which the predictors affect the hazard function in an additive manner rather than a multiplicative manner; and iii) the accelerated failure time (AFT), which is similar to the conventional linear regression model and therefore offers more flexibility in the understanding of covariates with non-constant effects on time-to-success. The individual effect of each predictor in the AFT model is interpreted in terms of TR, where the ratio denotes the acceleration factor. Unlike HR, when the TR assumes values greater than 1, this suggests that the event is less likely to occur, and when it is less than 1, it indicates that the event is more likely to occur. In general, the AFT model can be expressed as follows:

$$\ln(T) = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \ln(\varepsilon) \tag{5}$$

where $T$ is the time-to-event (or time-to-success) and $x_1, x_2 \cdots, x_n$, e $\beta_1$, $\beta_2 \cdots, \beta_n$ are the predictive variables and their estimated parameters, respectively. While $h_0(t)$ is the baseline hazard function (equation (4)), $(\varepsilon)$ is the error term, which is assumed to be a particular parametric distribution. Traditional regressions and the AFT model differ in the following ways: i) the predictive variables in the AFT model affect the time of the event multiplicatively; ii) the AFT model accommodates censored observations; and iii) the error term of the AFT model, even though it is independent and identically distributed (iid), does not follow a normal distribution. Some of the parametric distributions assumed in survival models include exponential, Weibull, generalized gamma, log-normal, and log-logistic distributions.

These are commonly used in place of a normal distribution (given that the event times have positive values and generally have a skewed distribution), making a normal symmetric distribution a poor choice to fit the data. Table 5 permits a comparison similar to that reported in Table 3: between the model with data censored by the platform (Censure 60) and the model that does not consider success on the last day of the campaign (Censure 59). However, in Table 5, parametric models are used. The distributions adopted by these models for the hazard function are in accordance with the conventional selection criteria of parametric models, and as a function of their respective AICs, these resulted in the selection of Weibull, log-logistic, and log-normal models. These models were also selected because they present the most appropriate statistical fit for the behavior of the distribution of our data and a proper preservation of their increasing relationship, as indicated in Fig. 3. Unlike the metric in the Cox proportional hazard models (PH) (Table 3), these models fall under the accelerated failure time (AFT) metric, or in other words, the time-to-success. This is why the values reported represent failure time ratios (TR), rather than hazard ratios (HR), as shown in Table 5.

For example, a failure time ratio of 1.48 for the fundraising target indicates an increase of 172%, which is capable of delaying the campaign's success (increasing survival) by 48%. Drawing a comparison of the estimates of the Weibull model for censure on the 60th day and the Log-logistic model for censure on the 59th day (the best models in each case according to the Akaike criteria - AIC), while an increase of 172% of the target or the number of pledgers is capable of contributing to the delay of 15.6% or acceleration of 16.4% of the success of the project for the first case, in the second case, these values increase to a delay of 48% or an acceleration of 32%.

In turn, the campaigns that offer greater rewards to sponsors present

**Table 4**
Test of the Violation of the Proportional Hazard (PH) Assumption.

| Variables | Log-rank Test |
|---|---|
| lnGoal | 2,782.07*** |
| lnPledges | 2,083.52*** |
| lnRewards | 94.44*** |
| Gini | 96.25*** |
| Popold | 1,590.27*** |
| Illiteracy | 1,491.96*** |
| Art | 4.88** |

Source: Calculation by the authors Note: This table presents the log-rank test for equality in the survivor function, that is, it verifies whether the assumption of constancy in the estimated parameters (PH) is violated. Based on this test, we can see that all of the analyzed variables presented variation within groups (observed vs. expected) over time; thus, the Cox model is not the most appropriate. ***$p < 0.01$ and **$p < 0.05$.

**Table 5**
Analysis of the Success Factors Based on Parametric Models.

| | Censure 60 (N = 4,262) | | | Censure 59 (N = 4,262) | | |
|---|---|---|---|---|---|---|
| | Weibull | LogLogistic | LogNormal | Weibull | LogLogistic | LogNormal |
| lnGoal | 1.156*** | 1.291*** | 1.354*** | 1.318*** | 1.480*** | 1.503*** |
| | (0.006) | (0.012) | (0.014) | (0.018) | (0.028) | (0.029) |
| lnPledges | 0.836*** | 0.770*** | 0.734*** | 0.730*** | 0.680*** | 0.666*** |
| | (0.004) | (0.006) | (0.007) | (0.010) | (0.011) | (0.012) |
| lnRewards | 1.070*** | 1.112*** | 1.153*** | 1.170*** | 1.168*** | 1.199*** |
| | (0.016) | (0.022) | (0.027) | (0.043) | (0.046) | (0.050) |
| Gini | 0.733*** | 0.493*** | 0.430*** | 0.333*** | 0.224*** | 0.216*** |
| | (0.075) | (0.064) | (0.066) | (0.090) | (0.061) | (0.062) |
| Art | 1.078*** | 1.178*** | 1.218*** | 1.265*** | 1.349*** | 1.372*** |
| | (0.015) | (0.022) | (0.026) | (0.041) | (0.047) | (0.051) |
| LR $chi^2$ | 1,909.15*** | 2,038.63*** | 2,186.73*** | 1,036.81*** | 1,224.13*** | 1,224.96*** |
| Log-Lik. | −1,401.00 | −1,554.67 | −1,772.83 | −2,339.36 | −2,230.15 | −2,242.05 |
| AIC | 2,816.01 | 3,123.35 | 3,559.67 | 4,692.72 | 4,474.30 | 4,498.11 |
| Failures (success) | 2,223 | 2,223 | 2,223 | 1,166 | 1,166 | 1,166 |

Source: Calculation by the authors Note: This table presents the estimated coefficients for the time to success of projects based on parametric models. The dependent variable was the time to success of the campaigns. The estimated models are in the same evaluation metric, that is, the accelerated failure time (AFT), with the coefficients expressed in time ratios. All variables are defined in Section 3. ***p < 0.01, **p < 0.05, *p < 0.1.

a delay in their time-to-success from 0.7% (Weibull for Censure 60) to 16.8% (Log-logistic for Censure 59). The campaigns located in areas with greater concentrations of income should have their time-to-success reduced from 26.7% (Weibull for Censure 60) to 77.6% (Log-logistic for Censure 59). Finally, artistic campaigns may suffer a delay in their time-to-success that ranges from 0.7% (Weibull for Censure 60) to 34.9% (Log-logistic for Censure 59), i.e., the non-artistic campaigns are more successful. The effects of the ln*Rewards*, *Gini*and *Art* covariates will also be in the same direction as the Cox estimates, and are found to be more expressive when using censure for the last day of the campaigns. In other words, the results suggest indications of the existence of a bias in traditional models (such as logit), which are caused by considering successful campaigns that depend on the late intervention of an informed agent interested in the success of the campaigns, the estimates

**Table 6**
Analysis of the Success Factors Based on the Parametric Models Considering Unobserved Heterogeneity.

| | Without Frailty (N = 4262) | | | With Frailty (N = 4262) | | |
|---|---|---|---|---|---|---|
| | Weibull | LogLogistic | LogNormal | Weibull | LogLogistic | LogNormal |
| Panel A: Time-to-success acceleration ratios for Censure 60 (for unobserved heterogeneity) | | | | | | |
| lnGoal | 1.156*** | 1.291*** | 1.354*** | 1.179*** | 1.291*** | 1.354*** |
| | (0.006) | (0.012) | (0.014) | (0.010) | (0.012) | (0.014) |
| lnPledges | 0.836*** | 0.770*** | 0.734*** | 0.823*** | 0.777*** | 0.734*** |
| | (0.004) | (0.006) | (0.007) | (0.006) | (0.006) | (0.007) |
| lnRewards | 1.070*** | 1.112*** | 1.153*** | 1.078*** | 1.112*** | 1.153*** |
| | (0.016) | (0.022) | (0.027) | (0.017) | (0.022) | (0.027) |
| Gini | 0.733*** | 0.493*** | 0.430*** | 0.681*** | 0.494*** | 0.432*** |
| | (0.075) | (0.064) | (0.066) | (0.074) | (0.064) | (0.067) |
| Art | 1.078*** | 1.178*** | 1.218*** | 1.096*** | 1.178*** | 1.218*** |
| | (0.015) | (0.022) | (0.026) | (0.017) | (0.022) | (0.026) |
| LR $chi^2$ | 1909.15*** | 2038.63*** | 2186.73*** | 1100.63*** | 1053.73*** | 1355.57*** |
| Log-Lik. | −1401.00 | −1554.67 | −1772.83 | −1395.88 | −1553.49 | −1772.01 |
| AIC | 2816.01 | 3123.35 | 3559.67 | 2807.76 | 3122.98 | 3560.02 |
| # of success | 2223 | 2223 | 2223 | 2223 | 2223 | 2223 |
| Panel B: Time-to-success acceleration ratios for Censure 59 (for unobserved heterogeneity) | | | | | | |
| lnGoal | 1.318*** | 1.480*** | 1.503*** | 1.539*** | 1.535*** | 1.557*** |
| | (0.018) | (0.028) | (0.029) | (0.029) | (0.029) | (0.321) |
| lnPledges | 0.730*** | 0.680*** | 0.666*** | 0.671*** | 0.673*** | 0.653*** |
| | (0.010) | (0.011) | (0.012) | (0.011) | (0.011) | (0.012) |
| lnRewards | 1.170*** | 1.168*** | 1.199*** | 1.154*** | 1.142*** | 1.188*** |
| | (0.043) | (0.046) | (0.050) | (0.045) | (0.043) | (0.050) |
| Gini | 0.333*** | 0.224*** | 0.216*** | 0.206*** | 0.201*** | 0.199*** |
| | (0.090) | (0.061) | (0.062) | (0.054) | (0.053) | (0.056) |
| Art | 1.265*** | 1.349*** | 1.372*** | 1.362*** | 1.333*** | 1.383*** |
| | (0.041) | (0.047) | (0.051) | (0.048) | (0.046) | (0.053) |
| LR $chi^2$ | 1036.81*** | 1224.13*** | 1224.96*** | 1300.67*** | 1303.75*** | 1260.54*** |
| Log-Lik. | −2339.36 | −2230.15 | −2242.05 | −2172.66 | −2164.62 | −2224.25 |
| AIC | 4692.72 | 4474.30 | 4498.11 | 4361.33 | 4345.24 | 4464.51 |
| # of success | 1166 | 1166 | 1166 | 1166 | 1166 | 1166 |

Source: Calculation by the authors Note: This table presents the estimated coefficients for the time-to-success of projects based on parametric models and unobserved heterogeneity models. The dependent variable was the duration of the campaign. The estimated models are in the same evaluation metric, that is, the accelerated failure time (AFT), with the coefficients expressed as time ratios (TR). Panel A presents a comparison including an estimated frailty parameter for 'Censure 60′. Panel B presents a comparison including an estimated frailty parameter for 'Censure 59′, which does not consider the failures (successes) that occur on the last day of the crowdfunding campaign. All variables are defined in Section 3. We controlled all estimates by inserting the connectivity variable, which indicates whether the region where the campaign was based had access to mobile broadband internet. We tried to control all the results reported in this table when considering the variable Connectivity (dummy variable with value = 1 when host cities of the campaigns had broadband internet coverage, and 0 otherwise); however, the results changed little and our estimates remained robust. ***p < 0.01, **p < 0.05, *p < 0.1.

of covariate effects, and the sense of underreporting these impacts.

### 4.5. Robustness tests and additional analysis

According to Liu (2014), for the identification of survival models, it is useful to consider two sources of variables in the duration data: i) variability resulting from the observable hazard factors in the model and ii) heterogeneity caused by the covariates that are not considered in the model, i.e., we would have a potential bias due to the omitted variable, one of the most frequent sources of endogeneity (Bhattacharjee et al., 2007). Unobserved heterogeneity may refer to, for example, the quality of the campaigns or the characteristics of their entrepreneurs.

Individual unobserved risks are termed "frailty" in a survival analysis. The unobserved frailty factor can be represented by a random effect ($\alpha_i$) that affects the hazard function in a multiplicative manner, $h(t|\alpha_i) = \alpha_i h(t)$. Keiding et al. (1997) and Lambert et al. (2004) have shown that the AFT model is more stable than the PH model in the presence of unobserved heterogeneity, given that the estimates for the parameters of AFT models are less affected by the choice of the probability distribution. In this study, we contemplate the unobserved heterogeneity found in campaigns in an unprecedented and robust manner. The treatment of unobserved heterogeneity was realized through the inclusion of a frailty parameter in the robust estimates presented in Panels A and B of Table 6. The estimated models in Panel A of Table 5 with censure on the 60th- and 59th day are reported in Panels A and B of Table 6, which can be compared to the models that include unobserved heterogeneity (models with frailty).

We can see from Table 6 that all of the reported estimates are in the same direction as the models presented above. Further, they are more significant in censuring the last day of the campaign. The greatest contrasts are related to ln*Goal*, ln*Rewards*, and *Gini* in any of the assumed distributions, i.e., Weibull, Log-logistic, or Log-normal. While it is difficult to determine the parameter that captures this heterogeneity, if some of the characteristics related to the quality of the project are being absorbed, this may explain the less relevant effect of rewards, given that when we control the quality of the project, the effect of rewards as a proxy tends to diminish. If the heterogeneity parameter captures some of the characteristics related to the predisposition to self-pledge (Crosetto & Regner, 2018), this would also explain the stronger effect of the fundraising target, the number of pledgers, and the income concentration, increasing the importance of the parsimonious choice concerning the value of the project in the proponent's contact network. The effects seem to be stronger, taking homogeneity into account for all the variables (in general).

## 5. Concluding remarks

This study contributes to the growing literature on crowdfunding. Based on our results, entrepreneurs, pledgers, and platform managers can learn from the time-to-success determinants of reward crowdfunding campaigns by particularly focusing on the influence of campaign attributes and location. The time-to-success of reward crowdfunding campaigns is estimated in a new manner using the survival analysis models. We employed a semi-parametric PH Cox model and a parametric AFT model. In addition, our results are robust when we consider unobserved heterogeneity models, which consider endogeneity effects because of the estimates biased by the omission of relevant covariates.

Crowdfunding allows the rise of new ventures that are unable to obtain financing through traditional means (Cornelius & Gokpinar, 2020; Hildebrand et al., 2017; Stanko & Henard, 2017). This is particularly relevant in environments characterized by high capital costs (Mendes-Da-Silva et al., 2016). We study a unique database covering more than 4200 campaigns initiated in 417 cities distributed across Brazil. They were all hosted on Catarse during the period 2011–2016, which raised more than R$ 38 million in reward crowdfunding campaigns during this period. The platform adopts the *all-or-nothing* system, where the entrepreneur receives "all" if the campaign is successful (reaches the funding target) and "nothing" in case of a failure. In our data, 52% of the campaigns were successful and 48% were failures, which is an interesting dataset to study the success of crowdfunding campaigns, determinants of their success, and time-to-success.

We found that the reward crowdfunding campaigns that achieve success more rapidly are those that are characterized by a lower target amount, a larger number of pledges, and a smaller number of rewards. Moreover, the higher and faster rates of success are predominantly found in non-art projects and are located in cities with greater income inequality. The interaction between both also shows that, for regions of higher inequality, non-art projects are preferred at a higher rate. Overall, the results show that the pledgers tend to prefer small projects located in areas with greater inequality, particularly non-art projects. This indicates that, more than compensation, pledgers are interested in the quality and purpose of projects and tend to invest in projects that may produce a positive social impact and contribute toward the reduction of inequality in the region.

In addition, we find that the covariates adopted in the empirical model influence the time-to-success in a non-constant manner during fundraising. This finding suggests the need to employ AFT models instead of the popular PH Cox model. In terms of the non-constant effect of the covariates, we have verified their behavior when we did not consider the campaigns that reached their target amount only on the last day of the fundraising period, when the agents with greater information in relation to the campaigns can act to secure the success of the campaigns. Such an agent may be an entrepreneur or even the owner of a reward crowdfunding platform (Crosetto & Regner, 2018). Our data do not allow us to test the evidence of self-funding, and we are not even sure if the contributions come directly from poor or rich people. However, we used unique data for the host cities of the campaigns in the largest crowdfunding platform of Brazil. Under the assumption of PH, Cox models on the one hand suggest that we can verify that the host city of campaigns exercises an economically stronger effect over time during the fundraising period. On the other hand, they suggest that the other covariates possess an essentially similar effect during the duration of the fundraising period, even though the tests conducted indicate that all of the covariates have a non-constant effect on time-to-success. The estimates obtained via the AFT models do not contradict the principal findings.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## References


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

AlliedCrowds (2016). Developing world crowdfunding prosperity through crowdfunding: Annual report. Available at: <https://gallery.mailchimp.com/0c95020f98fa983ee3aa6e710/files/AC_January_Report_Final.pdf>.

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. https://doi.org/10.1111/etap.12108.

Allison, T. H., Davis, B. C., Webb, J. W., & Short, J. C. (2017). Persuasion in crowdfunding: An elaboration likelihood model of crowdfunding performance. *Journal of Business Venturing, 32*(6), 707–725. https://doi.org/10.1016/j.jbusvent.2017.09.002.

Bai, L., & Gillen, D. (2017). Survival analysis via cox proportional hazards additive models. *Encyclopedia with Semantic Computing and Robotic Intelligence, 01*(01), 1650003. https://doi.org/10.1142/S2425038416500036.

Babin, B. J., Ortinau, D. J., Herrmann, J.-L., & Lopez, C. (2021). Science is about corroborating empirical evidence, even in academic business research journals. *Journal of Business Research, 126*, 504–511.

Beal, B. D., & Astakhova, M. (2017). Management and Income Inequality: A Review and Conceptual Framework. *Journal of Business Ethics, 142*(1), 1–23. https://doi.org/10.1007/s10551-015-2762-6.

Bhattacharjee, S., Gopal, R. D., Lertwachara, K., Marsden, J. R., & Telang, R. (2007). The effect of digital sharing technologies on music markets: A survival analysis of albums on ranking charts. *Management Science, 53*(9), 1359–1374. https://doi.org/10.1287/mnsc.1070.0699.

Bi, S., Liu, Z., & Usman, K. (2017). The influence of online information on investing decisions of reward-based crowdfunding. *Journal of Business Research, 71*, 10–18.

Box-Steffensmeier, J. M., & Zorn, C. J. W. (2001). Duration models and proportional hazards in political science. *American Journal of Political Science, 45*(4), 972. https://doi.org/10.2307/2669335.

Bradburn, M. J., Clark, T. G., Love, S. B., & Altman, D. G. (2003). Survival analysis part II: Multivariate data analysis–an introduction to concepts and methods. *British Journal of Cancer, 89*(3), 431–436.

Bretschneider, U., & Leimeister, J. M. (2017). Not just an ego-trip: Exploring backers' motivation for funding in incentive-based crowdfunding. *Journal of Strategic Information Systems, 26*(4), 246–260.

Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research, 24*(3), 499–519. https://doi.org/10.1287/isre.1120.0468.

Calic, G., & Mosakowski, E. (2016). Kicking off social entrepreneurship: How a sustainability orientation influences crowdfunding success. *Journal of Management Studies, 53*(5), 738–767. https://doi.org/10.1111/joms.12201.

Carlson, K. D., & Wu, J. (2012). The illusion of statistical control: Control variable practice in management research. *Organizational Research Methods, 15*(3), 413–435.

Chan, C. R., Park, H. D., Patel, P., & Gomulya, D. (2018). Reward-based crowdfunding success: Decomposition of the project, product category, entrepreneur, and location effects. *Venture Capital, 20*(3), 285–307. https://doi.org/10.1080/13691066.2018.1480267.

Chambers, D., McLaughlin, P. A., & Stanley, L. (2019). Barriers to prosperity: The harmful impact of entry regulations on income inequality. *Public Choice, 180*(1-2), 165–190.

Chemla, G., & Tinn, K. (2020). Learning through crowdfunding. *Management Science, 66*(5), 1783–1801. https://doi.org/10.1287/mnsc.2018.3278.

Chen, H., Gompers, P., Kovner, A., & Lerner, J. (2010). Buy local? The geography of venture capital. *Journal of Urban Economics, 67*(1), 90–102. https://doi.org/10.1016/j.jue.2009.09.013.

Cholakova, M., & Clarysse, B. (2015). Does the possibility to make equity investments in crowdfunding projects crowd out reward-based investments? *Entrepreneurship Theory and Practice, 39*(1), 145–172. https://doi.org/10.1111/etap.12139.

Clauss, T., Breitenecker, R. J., Kraus, S., Brem, A., & Richter, C. (2018). Directing the wisdom of the crowd: The importance of social interaction among founders and the crowd during crowdfunding campaigns. *Economics of Innovation and New Technology, 27*(8), 709–729.

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.

Cordova, A., Dolci, J., & Gianfrate, G. (2015). The determinants of crowdfunding success: Evidence from technology projects. *Procedia-Social and Behavioral Sciences, 181*, 115–124.

Cornelius, P. B., & Gokpinar, B. (2020). The role of customer investor involvement in crowdfunding success. *Management Science, 66*(1), 452–472. https://doi.org/10.1287/mnsc.2018.3211.

Costa, G. O. T., Machado, A. F., & Amaral, P. V. (2018). Vulnerability to poverty in Brazilian municipalities in 2000 and 2010: A multidimensional approach. *EconomiA, 19*(1), 132–148.

Courtney, C., Dutta, S., & Li, Y. (2017). Resolving information asymmetry: Signaling, endorsement, and crowdfunding success. *Entrepreneurship Theory and Practice, 41*(2), 265–290.

Crosetto, P., & Regner, T. (2014). Crowdfunding: Determinants of success and funding dynamics (No. 2014-035). Jena Economic Research Papers.

Crosetto, P., & Regner, T. (2018). It's never too late: Funding dynamics and self pledges in reward-based crowdfunding. *Research Policy, 47*(8), 1463–1477.

Da Cruz, J. V. (2018). Beyond financing: Crowdfunding as an informational mechanism. *Journal of Business Venturing, 33*(3), 371–393. https://doi.org/10.1016/j.jbusvent.2018.02.001.

De Larrea, G. L., Altin, M., & Singh, D. (2018). Determinants of success of restaurant crowdfunding. *International Journal of Hospitality Management, 78*, 150–158.

Defazio, D., Franzoni, C., & Rossi-Lamastra, C. (2021). How pro-social framing affects the success of crowdfunding projects: The role of emphasis and information crowdedness. *Journal of Business Ethics, 171*(2), 357–378. https://doi.org/10.1007/s10551-020-04428-1.

de Loyola Hummell, B. M., Cutter, S. L., & Emrich, C. T. (2016). Social vulnerability to natural hazards in Brazil. *International Journal of Disaster Risk Science, 7*(2), 111–122.

Demir, A., Pesqué-Cela, V., Altunbas, Y., & Murinde, V. (2020). Fintech, financial inclusion and income inequality: A quantile regression approach. *The European Journal of Finance*. https://doi.org/10.1080/1351847X.2020.1772335.

Eiteneyer, N., Bendig, D., & Brettel, M. (2019). Social capital and the digital crowd: Involving backers to promote new product innovativeness. *Research Policy, 48*(8), 103744. https://doi.org/10.1016/j.respol.2019.01.017.

Efron, B. (1988). Logistic regression, survival analysis, and the Kaplan-Meier curve. *Journal of the American statistical Association, 83*(402), 414–425. https://www.jstor.org/stable/2288857.

Ethiraj, S., Gambardella, A., & Helfat, C. (2016). Replication in strategic management. *Strategic Management Journal, 37*(11), 2191–2192. https://doi.org/10.1002/smj.2581.

Florida, R. (2002). The economic geography of talent. *Annals of the Association of American geographers, 92*(4), 743–755. https://doi.org/10.1111/1467-8306.00314.

Florida, R. (2014). *The rise of the creative class—revisited: Revised and expanded*. Basic books.

Frydrych, D., Bock, A. J., Kinder, T., & Koeck, B. (2014). Exploring entrepreneurial legitimacy in reward-based crowdfunding. *Venture Capital, 16*(3), 247–269. https://doi.org/10.1080/13691066.2014.916512.

Gamble, J. R., Brennan, M., & McAdam, R. (2017). A rewarding experience? Exploring how crowdfunding is affecting music industry business models. *Journal of Business Research, 70*, 25–36. https://doi.org/10.1016/j.jbusres.2016.07.009.

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction, 20*(6), 1–32. https://doi.org/10.1145/2530540.

Giudici, G., Guerini, M., & Rossi-Lamastra, C. (2013). Why crowdfunding projects can succeed: the role of proponents' individual and territorial social capital. https://doi.org/10.2139/ssrn.2255944.

Giudici, G., Guerini, M., & Rossi-Lamastra, C. (2017). Reward-based crowdfunding of entrepreneurial projects: The effect of local altruism and localized social capital on proponents' success. *Small Business Economics, 50*(2), 307–324. https://doi.org/10.1007/s11187-016-9830-x.

Glazer, A., & Konrad, K. A. (1996). A signaling explanation for charity. *The American Economic Review, 86*(4), 1019–1028. https://www.jstor.org/stable/2118317.

Grüner, H. P., & Siemroth, C. (2019). Crowdfunding, Efficiency, and inequality. *Journal of the European Economic Association, 17*(5), 1393–1427. https://doi.org/10.1093/jeea/jvy023.

Hasanov, F., & Izraeli, O. (2011). Income inequality, economic growth, and the distribution of income gains: Evidence from the U.S. States. *Journal of Regional Science, 51*(3), 518–539. https://doi.org/10.1111/j.1467-9787.2010.00700.x.

Hemer, J. (2011). A snapshot on crowdfunding (No. R2/2011). Working papers firms and region.

Hildebrand, T., Puri, M., & Rocholl, J. (2017). Adverse incentives in crowdfunding. *Management Science, 63*(3), 587–608. https://doi.org/10.1287/mnsc.2015.2339.

Hobbs, J., Grigore, G., & Molesworth, M. (2016). Success in the management of crowdfunding projects in the creative industries. *Internet Research, 26*(1), 146–166. https://doi.org/10.1108/IntR-08-2014-0202.

Hörisch, J. (2015). Crowdfunding for environmental ventures: An empirical analysis of the influence of environmental orientation on the success of crowdfunding initiatives. *Journal of Cleaner Production, 107*, 636–645. https://doi.org/10.1016/j.jclepro.2015.05.046.

Hörisch, J. (2018). 'Think big'or'small is beautiful'? An empirical analysis of characteristics and determinants of success of sustainable crowdfunding projects. *International Journal of Entrepreneurial Venturing, 10*(1), 111–129. https://doi.org/10.1504/IJEV.2018.090982.

Hosmer, D. W., Lemeshow, S., & May, S. (2008). Parametric regression models. In N. J. Hoboken (Ed.), *Applied Survival Analysis* (2nd ed., pp. 244–285). John Wiley & Sons.

Hu, M., Li, X., & Shi, M. (2015). Product and pricing decisions in crowdfunding. *Marketing Science, 34*(3), 331–345. https://doi.org/10.1287/mksc.2014.0900.

Josefy, M., Dean, T. J., Albert, L. S., & Fitza, M. A. (2017). The role of community in crowdfunding success: Evidence on cultural attributes in funding campaigns to "save the local theater". *Entrepreneurship Theory and Practice, 41*(2), 161–182. https://doi.org/10.1111/etap.12263.

Keiding, N., Andersen, P. K., & Klein, J. P. (1997). The role of frailty models and accelerated failure time models in describing heterogeneity due to omitted covariates. *Statistics in Medicine, 16*(2), 215–224. https://doi.org/10.1002/(SICI)1097-0258(19970130)16:2<215::AID-SIM481>3.0.CO;2-J.

Kim, K., & Hann, I. H. (2014). Crowdfunding and the democratization of access to capital: a geographical analysis. Robert H. Smith School Research Paper.

Kimura, F., Hagihara, K., Horie, N., & Asahi, C. (2018). Supporting organization for social enterprises: Intermediate organization case. *Studies in Regional Science, 48*(1), 51–70. https://doi.org/10.2457/srs.48.51.

Koch, J.A., & Siering, M. (2015). Crowdfunding success factors: the characteristics of successfully funded projects on crowdfunding platforms. In: Proceedings of the 23rd European Conference on Information Systems (ECIS), Muenster, Germany.
Kleinbaum, D. G., & Klein, M. (2010). *Survival analysis*: A self-learning text. *Springer Science & Business Media*. https://doi.org/10.1007/978-1-4419-6646-9.
Knudsen, B., Florida, R., Gates, G., & Stolarick, K. (2007). Urban density, creativity and innovation.
Krugman, P. (1992). *Geography and trade*. Cambridge, MA: MIT Press.
Lagazio, C., & Querci, F. (2018). Exploring the multi-sided nature of crowdfunding campaign success. *Journal of Business Research, 90*, 318–324. https://doi.org/10.1016/j.jbusres.2018.05.031.
Lambert, T., & Schwienbacher, A. (2010). *An empirical analysis of crowdfunding*. Louvain-la-Neuvwe: Louvain School of Management, Catholic University of Louvain.
Lambert, P., Collett, D., Kimber, A., & Johnson, R. (2004). Parametric accelerated failure time models with random effects and an application to kidney transplant survival. *Statistics in Medicine, 23*(20), 3177–3192. https://doi.org/10.1002/(ISSN)1097-025810.1002/sim.v23:2010.1002/sim.1876.
Landström, H., Parhankangas, A., Mason, C. (2019). Handbook of research on crowdfunding (1st ed.). Northampton: Edward elgar Publishing. doi: 10.4337/9781788117210.
La Porta, R., & Shleifer, A. (2014). Informality and development. *Journal of Economic Perspectives, 28*(3), 109–126. https://doi.org/10.1257/jep.28.3.109.
Lee, C. H., & Chiravuri, A. (2019). Dealing with initial success versus failure in crowdfunding market: Serial crowdfunding, changing strategies, and funding performance. *Internet Research, 29*(5), 1190–1212. https://doi.org/10.1108/INTR-03-2018-0132.
Li, Y., Rakesh, V., & Reddy, C. K. (2016). Project success prediction in crowdfunding environments. In *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining* (pp. 247–256). https://doi.org/10.1145/2835776.2835791.
Lin, M., Prabhala, N. R., & 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), 17–35. https://doi.org/10.1287/mnsc.1120.1560.
Liu, X. (2014). Survival models on unobserved heterogeneity and their applications in analyzing large-scale survey data. *Journal of Biometrics & Biostatistics, 5*(2), 1000191.
Mantel, N. (1966). Evaluation of survival data and two new rank order statistics arising in its consideration. *Cancer Chemotherapy Reports, 50*, 163–170.
Mendes-Da-Silva, W., Rossoni, L., Conte, B. S., Gattaz, C. C., & Francisco, E. R. (2016). The impacts of fundraising periods and geographic distance on financing music production via crowdfunding in Brazil. *Journal of Cultural Economics, 40*(1), 75–99. https://doi.org/10.1007/s10824-015-9248-3.
Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. *Journal of Business Venturing, 29*(1), 1–16. https://doi.org/10.1016/j.jbusvent.2013.06.005.
Mollick, E.R. & Kuppuswamy, V. (2014). After the campaign: Outcomes of crowdfunding. UNC Kenan-Flagler Research Paper, (2376997).
Naar, A. (2016). Feeling good about feeling good: Investor selection in a pro-social crowdfunding context. In 76th Annual Meeting of the Academy of Management. doi: 10.5465/ambpp.2016.17523abstract.
Ohno-Machado, L. (2001). Modeling medical prognosis: Survival analysis techniques. *Journal of Biomedical Informatics, 34*(6), 428–439. https://doi.org/10.1006/jbin.2002.1038.
Oo, P. P., Allison, T. H., Sahaym, A., & Juasrikul, S. (2019). User entrepreneurs' multiple identities and crowdfunding performance: Effects through product innovativeness, perceived passion, and need similarity. *Journal of Business Venturing, 34*(5), 105895. https://doi.org/10.1016/j.jbusvent.2018.08.005.
Ordanini, A., Miceli, L., Pizzetti, M., & Parasuraman, A. (2011). Crowdfunding: Transforming customers into investors through innovative service platforms. *Journal of Service Management, 22*(4), 443–470. https://doi.org/10.1108/09564231111155079.
Parhankangas, A., & Renko, M. (2017). Linguistic style and crowdfunding success among social and commercial entrepreneurs. *Journal of Business Venturing, 32*(2), 215–236.
van de Rijt, A., Kang, S. M., Restivo, M., & Patil, A. (2014). Field experiments of success-breeds-success dynamics. *Proceedings of the National Academy of Sciences of the United States of America, 111*, 6934–6939.
Savage, I. R. (1956). Contributions to the theory of rank order statistics-the two-sample case. *The Annals of Mathematical Statistics, 27*(3), 590–615.
Schelling, T. C. (1978). *Micromotives and macrobehavior*. New York: W.W. Norton.
Scholz, N. (2015). *The relevance of crowdfunding: The impact on the innovation process of small entrepreneurial firms*. Springer.
Scott-Briggs, A. (2017). Crowdfunding grows up as VC activity declines. Available at: https://www.techbullion.com/crowdfunding-grows-vc-activity-declines/.
Shi, M., & Guan, L. (2016). An empirical study of crowdfunding campaigns: Evidence from Jing Dong crowdfunding platform. In 2016 13th International Conference on Service Systems and Service Management (ICSSSM) (p. 1–5). IEEE. doi: 10.1109/ICSSSM.2016.7538637.
Skirnevskiy, V., Bendig, D., & Brettel, M. (2017). The influence of internal social capital on serial creators' success in crowdfunding. *Entrepreneurship Theory and Practice, 41*(2), 209–236.
Stanko, M. A., & Henard, D. H. (2017). Toward a better understanding of crowdfunding, openness and the consequences for innovation. *Research Policy, 46*(4), 784–798.
Steinberg, D. (2012). The kickstarter handbook. Real-life Crowdfunding success stories.
Stiglitz, J. E. (2012). Macroeconomic fluctuations, inequality, and human development. *Journal of Human Development and Capabilities, 13*(1), 31–58. https://doi.org/10.1080/19452829.2011.643098.
Strausz, R. (2017). A theory of crowdfunding - A mechanism design approach with demand uncertainty and moral hazard. *American Economic Review, 107*(6), 1430–1476.
Tsang, E. W., & Kwan, K. M. (1999). Replication and theory development in organizational science: A critical realist perspective. *Academy of Management Review, 24*(4), 759–780.
Vincens, N., & Stafström, M. (2015). Income inequality, economic growth and stroke mortality in Brazil: Longitudinal and regional analysis 2002–2009. *PLoS ONE, 10*(9), e0137332.
Vismara, S. (2018). Signaling to overcome inefficiencies in crowdfunding markets. In D. Cumming, & L. Hornuf (Eds.), *The economics of crowdfunding* (pp. 29–56). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-66119-3_3.
Vukovic, M., Lopez, M., & Laredo, J. (2010). People cloud for the globally integrated enterprise. In Service-Oriented Computing. ICSOC/ServiceWave 2009 Workshops (pp. 109–114). Berlin Heidelberg: Springer. doi: 10.1007/978-3-642-16132-2_10.
Wang, N., Li, Q., Liang, H., Ye, T., & Ge, S. (2018). Understanding the importance of interaction between creators and backers in crowdfunding success. *Electronic Commerce Research and Applications, 27*, 106–117. https://doi.org/10.1016/j.elerap.2017.12.004.
*World Bank*. *World Development Indicators database*. (2019). Available at: https://databank.worldbank.org/data/download/GDP.pdf.
Yang, J., Liu, L., & Yin, C. (2019). A non-liner decision model for green crowdfunding project success: Evidence from China. *International Journal of Environmental Research and Public Health, 16*(2), 187. https://doi.org/10.3390/ijerph16020187.
Yeh, T.-L., Chen, T.-Y., & Lee, C.-C. (2019). Investigating the funding success factors affecting reward-based crowdfunding projects. *Innovation, 21*(3), 466–486. https://doi.org/10.1080/14479338.2019.1585191.
Zaggl, M. A., & Block, J. (2019). Do small funding amounts lead to reverse herding? A field experiment in reward-based crowdfunding. *Journal of Business Venturing Insights, 12*, e00139. https://doi.org/10.1016/j.jbvi.2019.e00139.
Zhang, M. (Ed.). (2009). *Competitiveness and growth in Brazilian cities: local policies and actions for innovation*. World Bank Publications. https://doi.org/10.1596/978-0-8213-8157-1.
Zhou, M., Lu, B., Fan, W., & Wang, G. A. (2018). Project description and crowdfunding success: An exploratory study. *Information Systems Frontiers, 20*(2), 259–274.
Zvilichovsky, D., Inbar, Y., & Barzilay, O. (2015). Playing both sides of the market: Success and reciprocity on crowdfunding platforms. Available at SSRN: https://ssrn.com/abstract=2304101.

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