Janků, Jan; Kučerová, Zuzana; Dařena, František

Article

Behavioral insights from crowdfunding financing : what do social media ties, emotional cues and sentiment tell us?

Ekonomický časopis

Behavioral Insights from Crowdfunding Financing: What Do Social Media Ties, Emotional Cues and Sentiment Tell Us?[1]

Jan JANKŮ – Zuzana KUČEROVÁ** – František DAŘENA****

Abstract

The aim of this paper is to identify the factors that contribute to the successful funding of crowdfunding projects, with a focus on conventional, social media and affective factors. Our unique dataset contains 267,830 Kickstarter projects from the U.S., Australia, Canada, the U.K., and Europe. In addition to determinants based on conventional factors, we study the textual characteristics of a project's description and comments, including sentiment and emotional cues, extracted using a web scraper. We find that social media factors (such as social networks, comments on projects, the experience and social media capital of the project founder) as well as affective factors (emotional cues and sentiment related to project description) influence the success of projects in addition to the conventional determinants such as the funding goal, funding project duration, and project category. Our results are stable when we control for partial time periods, the geographic origin of the founder, and the founder's social media capital and experience.

Keywords: *crowdfunding, behavior, emotional cues, sentiment, text analysis*

JEL Classification: C55, D22, D91, L86

DOI: https://doi.org/10.31577/ekoncas.2023.02.01

Article History: *Received*: November 2022 *Accepted*: April 2023

---

* Jan JANKŮ, VSB-Technical University of Ostrava, Faculty of Economics, Sokolská tř. 33, 702 00 Ostrava, Czech Republic; e-mail: jan.janku@vsb.cz; Czech National Bank, Na Příkopě 864/28, 115 03 Praha 1, Czech Republic; e-mail: jan.janku@cnb.cz

Disclaimer: The views expressed are those of the author and not necessarily those of the Czech National Bank.

** Zuzana KUČEROVÁ, corresponding author, VSB-Technical University of Ostrava, Faculty of Economics, Sokolská tř. 33, 702 00 Ostrava, Czech Republic; Mendel University in Brno, Faculty of Business and Economics, Zemědělská 1, 613 00 Brno, Czech Republic; e-mail: zuzana.kucerova@vsb.cz

*** František DAŘENA, Mendel University in Brno, Faculty of Business and Economics, Zemědělská 1, 613 00 Brno, Czech Republic; e-mail: frantisek.darena@mendelu.cz

[1] This work was supported by the Czech Science Foundation under grant number 17-25924S, *Comparative Study of Crowdfunding Projects in EU: Access to Finance, Risks and Regulation*.

Introduction

Crowdfunding is a type of crowdsourcing, that involves collecting many small monetary contributions to finance an enterprise or a particular product. In the era of advanced information technologies, crowdfunding financing is a new, smart, and quick way of raising funds by interconnecting a large number of investors (funders) throughout the world with a large number of entrepreneurs or just individuals (project founders) seeking funds for their potential projects. Generally, there are four main types of crowdfunding models: donation-based, reward-based, lending-based, equity-based. In our paper, we analyze projects of the Kickstarter platform providing reward-based financing. When trading through crowdfunding platforms, both funders and founders typically lack experience and proper financial education. As such, the success of crowdfunding financing depends on factors other than strictly economic ones, such as social media influence and various affective factors.

In our paper, we aim to show how these factors, particularly social media ties, emotional cues, and sentiment, can impact the success of the financing campaign in crowdfunding platforms.

Our dataset of Kickstarter crowdfunding projects collected from April 2009 to July 2017 includes 267,830 projects from the U.S., Australia, Canada, the U.K., and Europe. We focus on individual crowdfunding projects and their characteristics (microdata). Moreover, we also use unique data extracted using a web scraper, specifically created to extract data from the Kickstarter server. To determine the positive or negative emotional cues and sentiment contained in the text concerning individual projects, we use text analysis and the Valence Aware Dictionary and Sentiment Reasoner (VADER) algorithm.

Our paper contributes to the literature on the determinants of successful crowdfunding projects in several ways. First, we join an empirical strand of research focused on conventional incentive-based factors of behavior (see, e.g., Mollick, 2014, or Barbi and Bigelli, 2017) and take a step forward by adding behavioral factors. We hypothesize that social media and affective factors have an important impact on the success of crowdfunding financing (Hypothesis 1). Our results indicate that social media factors, such as a creator's social media capital and experience, or having many positive comments from other contributors, positively influence the chances of success. We also find that affective factors, i.e., emotional cues (the use of specific words or phrases in the project description that prompt a certain emotional response), strongly influence the investment decisions of contributors. We show that negative emotional cues (fear, anxiety, and despair) can decrease the probability of funding success more than positive emotional cues (enthusiasm, gratitude, and humility). We also point out that behavioral and conventional approaches cannot be completely differentiated and we offer alternative interpretations for several factors of crowdfunding success. Second, we provide control measures for other factors and perform a battery of robustness checks that further increase the explanatory power of our research. We hypothesize that the role of factors influencing crowdfunding success evolves over time (Hypothesis 2). The current literature has not been devoted to different time windows and their specifics yet, which may be our further contribution to current knowledge.

Some authors provide control measures for the geographic distribution of non-U.S. projects and the diffusion across countries (Mollick, 2014; Barbi and Bigelli, 2017), local and distant contributors (Agrawal et al., 2015). However, we hypothesize that there are no significant regional differences concerning factors of crowdfunding financing (Hypothesis 3). We show that the factors of success of projects from the U.S., Australia, Canada, the U.K., and Europe are consistent with those in the U.S., which may defend our results against the objection that they are geographically conditioned.

Next, we use control measures for founders' growing social media capital and experience. Here, we hypothesize that social media capital and past experience of project founders have an impact on the crowdfunding campaign (Hypothesis 4). We state that founders who have experience with previous projects are more successful than those without any previous experience and add that every other previous project increases the chances of success.

Third, we construct and use our own sentiment and emotional cues measures to analyze the textual description of crowdfunding projects, while taking the characteristics of specific project categories into account (for the analysis of textual information, see, e.g., Yuan et al., 2016; Rhue and Clark, 2018 or Rhue and Robert, 2018). We hypothesize that sentiment and emotional cues in the project text description increase the success of crowdfunding financing (Hypothesis 5). We show that specific negative emotional cues and comments have the most significant influence on the success of crowdfunding as they can significantly limit the confidence of other potential contributors.

1. Literature Review

1.1. Conventional Determinants of Successful Crowdfunding Projects

Generally, the success of reward-based crowdfunding projects depends on basic project properties, such as the funding goal, the project duration, or the project category. Many empirical studies show that having a higher funding goal is associated with greater success of projects (see, e.g., Mollick, 2014; Barbi and Bigelli, 2017). Concerning the funding period, the picture is not so clear; some authors find that a longer the duration of the project increases the probability of success (Cordova et al., 2015), while other authors find no effect (Colombo et al., 2015; Koch and Siering, 2015).

However, there are also studies that show that longer project duration actually reduces the chances of successful financing (Mollick, 2014 or Skirnevskiy et al., 2017). This literature is consistent with the general recommendation of Kickstarter, which encourages shorter funding periods because they increase the confidence and motivation of potential funders.

1.2. Social Media Factors

As Alegre and Moleskis (2016, p. 29) state, individual funders' decision-making is influenced by behavioral factors, which could be a crucial feature for campaign success. People live in an era of information, and behavior can be significantly affected by their relationships and network connections (see, e.g., Bourdieu, 1986; Coleman, 1988; Portes, 1998; Lin et al., 2019). We refer to the variables that capture the influence of the social media environment as "social media factors".

Etter et al. (2013) distinguish between social media data (such as the number of tweets or fans) and conventional data from Kickstarter (including project category, funding goals, duration, and number of backers). They find that social media factors predict project success with lower accuracy than indicators from Kickstarter, but recommend combining both sets of indicators in one predictive model. Other social media determinants, including website presence, social network connections, and the number of positive or negative comments, updates, or blog entries are also occasionally incorporated into empirical analyses. Mollick (2014), Kraus et al. (2016) and Kaur and Gera (2017) find that web tools can attract interest from potential contributors. Using data from German projects on the Startnext platform (Crosetto and Regner, 2015) or U.S. projects on the Kickstarter platform (Barbi and Bigelli, 2017), authors also examine both conventional determinants and indicators of a project's communication between a project creator and its contributors (such as video presentation, blog entries, and the length of a project description). They conclude that these social media determinants can ensure the success of crowdfunding projects.

De Larrea et al. (2019) study a sample of restaurant Kickstarter projects in the U.S. and confirm the significant impact of social media determinants such as project presentation to the community, communication through images and information updates, and responsiveness to funders' comments. Zheng et al. (2014)

find that social networks (as a specific form of multidimensional social capital) positively influence knowledge sharing among people and reciprocal exchanges between founders and contributors facilitating the success of crowdfunding projects in both the U.S. and China, where communication via social networks plays a significant role.

1.3. Affective Behavioral Factors

In addition to social media factors, the success of crowdfunding project financing can also be influenced by the emotional cues that a given project can evoke. Appealing to emotions by project creators and eliciting specific emotional states or affects may contribute to crowdfunding success.

Textbook rational economic beings (or *homo oeconomicus*) strictly make decisions only in response to economic incentives. However, real humans respond to a variety of other stimuli, and their decisions are intertwined with emotions (Thaler and Sunstein, 2008). Behavioral research shows that many individual choices cannot be explained as being consistent with the neo-classical axioms of rational behavior (see, e.g., Tversky and Kahneman, 1974). People are often affected by images that carry positive or negative markers. The idea that the first impression can (often subliminally) influence a human judgment is based on dual-process models mentioned in Epstein (1994) and Sloman (1996). These two processes are intuition and reason and we focus here on the former one. Emotional and economic incentives cause conflict in decision-making environments and deliberative neural processes must be engaged to regulate automatic emotional reactions to make economically desirable decisions (Farrell, Goh and White, 2018; Hansen, 2016). Given that reward-based crowdfunding is often pursued by non-professional investors who may rely more on "gut feelings" than thorough economic knowledge, we hypothesize that emotional factors may play a significant role in the decision to invest in or support a crowdfunding project.

Human behavior results from the natural limitations of the experiential (intuitive) system and the existence of stimuli in a person's environment that are simply not amenable to valid affective representation (see, e.g., Zajonc, 1980; Finucane et al., 2000). Human cognitive processes (and their outcomes) are influenced by affects and emotions. These determinants of decision-making can be called (with some simplification) "affective factors".

Simon (1957), Tversky and Kahneman (1974), and other authors offer alternative theories and models of decision-making but all these alternatives are based on the idea that human decision-making is primarily influenced by cognition. Only rarely do authors focus on an important component of human judgement and decision-making: an affect.

Finucane et al. (2000) therefore define 'affect' as an emotional state that people experience, such as happiness or sadness associated with a certain stimulus. Mowrer (1960) states that our responses to some incentives are also conditioned by emotions such as hope or fear which serve as motivational states that subsequently lead to action. Damasio (1994) adds that human thinking is largely influenced by images or words that are marked by positive and negative emotions due to life experience. Therefore, the first impression can (often subliminally) influence a human judgement (Epstein, 1994; Sloman, 1996).

We assume that people's decisions to invest in crowdfunding can easily be influenced by feelings or emotional cues evoked by reading the project description. Like Slovic et al. (2007), we state that intuitive thinking can lead investors to alter their responses in a way that enables the deliberate manipulation of investors' affective responses by those who want to control their behavior (e.g., project founders).

Only a few studies focus on analyzing of the textual information to identify sentiment and emotional cues contained in texts concerning reward-based crowdfunding projects. Yuan et al. (2016) study the textual information in the description of crowdfunding projects and apply machine-learning methods to analyze the impact of selected variables on the success of projects on Chinese crowdfunding platforms.

According to the authors, features drawn from the project description are not the most influential factors in funding success. Conversely, Wang et al. (2018) and Jiang et al. (2020) verify the positive impact of both comment quantity and sentiment on success in projects on a Chinese platform. Parhankangas and Renko (2017) find that the linguistic style of crowdfunding texts influences project success on the Kickstarter platform, particularly in the case of social entrepreneurs. Zhou et al. (2018) analyze the impact of project description on funding success and confirm that variables concerning project description (length, readability, and tone) can increase the predictive power of a basic model on the determinants of success in the case of Kickstarter projects.

In our paper, we not only measure the sentiment of project descriptions and its impact on project success, but we also add the impact of positive/negative emotional cues embodied in the text and compare them.[2]

We also show that negative comments from contributors can reduce confidence in a project that is already partially funded and almost achieves success in the form of full funding.

[2] For our definition of sentiment and emotional cues, see section *Factors Selection and Description*.

2. Factors Selection and Description

We investigate the factors that contribute to the success of a particular project. A successfully financed project means that the project has received all the required financial funding before the project deadline. Because Kickstarter offers funding on an all-or-nothing basis, if the project does not reach its goal, it is closed as unsuccessful, and the pledges are returned to contributors. The data has been collected and processed as part of a larger research program on crowdfunding.

In this section, we provide a description of the variables used in our analysis. The distinction between conventional, social media, and affective factors reflects their characteristics as well as our desire to increase the readability of the text. If any of the factors may partially fall into a category other than the one, we have defined, we draw attention to this point in the text. Our original dataset comprises data over eight years with more than 140 project characteristics. From these 140 characteristics, we selected those relevant to our research based on the above literature review of empirical and theoretical literature. Concise information about the data is in Appendix A. Appendix B contains a correlation matrix of our independent variables.

2.1. Conventional Factors

We define conventional factors as variables that influence the behavior of investors (funders) as economic agents who correctly weigh costs and benefits, maximizing their subjective utility by financing chosen projects. These projects are the best for *investors* in terms of material benefits, risk, and time for delivery. From the point of view of mainstream economics, we consider these variables as traditional or conventional.

First, we include the variables used by other studies on this topic (see Mollick, 2014; Colombo et al., 2015; Koch and Siering, 2015). The variable log_goal_i is the logarithm of the goal amount for project i. We assume that rational contributors evaluate projects based on the probability of achieving financial goals, and larger projects are usually treated as riskier. We therefore assume that a larger project goal has a negative impact on funding success.

The variable $duration_i$ measures the number of days during which the project accepts pledges. Kickstarter allows a funding period from 1 to 60 days. Shorter periods can create more urgency and motivate people to invest. Additionally, longer funding periods can lead backers to procrastinate and postpone their contributions. We therefore assume that the shorter the duration, the higher the probability of funding success. We also approximate the preparation period of the individual project i. The variable $preparation_i$ is the time that elapses between the day the founder started working on the project on Kickstarter and the day the funding campaign was launched. A longer preparation period could indicate a higher-quality project, and we therefore assume that it has a positive impact on funding success.

We also use control measures for the structure of financing opportunities offered to potential backers. Each project can set up many reward levels requiring various pledges (the amount of money to be pledged or contributed in the future) from very low to high sums of money. To estimate the effect of pledges of various sizes, we measure the average pledge option ($avg\_pledge\_opt_i$) calculated as the mean of pre-set financing options for backers (in U.S. dollars). We also measure the number of pledge options ($num\_pledge\_opt_i$) for backers. A higher number of pledging options might increase the probability of project success, and a higher average amount of money to be pledged might decrease the probability of success.

The overall quality and appearance of the project can also attract contributors. We therefore control the number of images describing the project ($images_i$), the number of other multimedia elements, such as audio and video ($media_i$), the number of words describing the project in the main text ($words\_text_i$), and the number of words describing the project in the blurb ($words\_blurb_i$).[3] We view these factors as conventional because they reflect the visual and textual quality of *the particular project* being evaluated. Like the other variables in this category, they largely reflect how much the founder of the project has devoted to its optimal setup and presentation.

Even completely rational people have little willingness to abstain from consuming now because of the higher intensity of present desires. Pigou (1920) calls this phenomenon "a defective telescopic faculty", which indicates a strong preference for present pleasures and seeing future pleasures on a diminishing scale. We therefore check for an average time to delivery ($delivery\_time_i$), indicating the number of days that elapse before the promised goods or services are delivered.

2.2. Social Media Factors

As mentioned above, we consider factors that operate in the social environment in which both the founders and backers exist. First, we measure the previous experience and social media capital of a founder using the dummy variable $creator\_capital_i$. Creators of projects are not limited to creating only one project

[3] A blurb is a paragraph that briefly describes the goal of a crowdfunding project at the beginning of the project description.

during the funding process. With previous projects already funded, they attract a group of fans and potential future backers (see Butticè et al., 2017). Our control variable takes a value of one for a project that has a better-known founder (a founder with more than one earlier project on Kickstarter) and zero otherwise. Alternatively, in a robustness check, we also measure the variable $creator\_capital2_i$, which indicates the number of previous successful projects (e.g., two in the case of a third project of the individual founder, three in the case of a fourth project of the same founder). We do not see this factor as conventional because it is not related to the quality of each specific project but to the quality of the creator's past projects. We assume that the creator becomes more well-known due to successful past projects, and his/her familiarity is a social factor distributed through social media.[4]

We also approximate the breadth of the social environment with the variable $social\_media_i$. This ordinal variable records the number of social networking sites that mention a particular project. For this purpose, we consider Facebook, Twitter, Instagram, and YouTube. If the individual project refers to all these networks, the variable takes a value of four. It is necessary to mention that this variable probably does not capture solely the breadth of a social media environment. Projects linked to more social media platforms attract more funders because the more media outlets a project has, the more it is likely to be seen by more people. In the traditional approach, this can be seen as simple advertising (to strangers) and not leveraging one's own social ties.

Because electronic word-of-mouth communication (see Hennig-Thurau et al., 2004) among founders on social networks or on a specific platform can also influence their behavior, we measure the number of positive comments by other contributors ($num\_positive\_comm\_cont_i$). Therefore, we consider only comments made before the deadline of individual projects, i.e., in the period when investors can pledge money to a specific project before the platform closes it down. As a robustness check, we also examine the influence of negative comments ($num\_negative\_comm\_cont_i$). We classify the number of positive and negative comments as social media factors because they are not affective factors that can be directly influenced by the respective project creator. At the same time, we do

[4] It is a matter of discussion as to whether our variable measures the social media capital of the founder (i.e., a group of fans gained during the previous crowdfunding campaigns) or their experience (i.e., with every project they know what to do and how to advertise their campaign better). If the variable measures the founder's experience, one can argue that this sign of an experienced founder should be rather a conventional factor. Completely rational individuals probably invest more in projects that are more likely to be realized, and experienced founders constantly record a higher probability of success. However, social media capital gained during previous crowdfunding campaigns is something that matters rather in the field of the behavioral approach, where individuals not only calculate costs and benefits but also care about their community and social ties.

not evaluate the sentiment (or valence) of these comments but only their number. We, therefore, prefer not including them in the affective factors.

2.3. Affective Factors

The variables $sentiment\_comm\_creator_i$, $sentiment\_text_i$, and $emotions\_positive_i$ form a group of affective factors: $sentiment\_comm\_creator_i$ and $sentiment\_text_i$ describe a sentiment measured in all creators' (founders') comments before the deadline, respectively, in the text of the main project description. In this way, the creator can influence potential funders. The sentiment is measured on a scale from –1 to 1 (the higher the value, the more positive the sentiment). We refer to our variable as "sentiment" given that the extant economic literature labels similarly constructed variables in the same way. However, the psychology literature uses the term "valence" instead.[5]

Finally, $emotions\_positive_i$ is the sum of words in the project's text that prompt positive emotional responses. Let us make it clear at this point that given the nature of our variables, it is impossible to make any claims about the real emotional state of people reading a project's content and, ultimately, investing in it. Our variables, instead, reflect emotional cues rather than emotions. These emotional cues are defined as emotional states characterized by the presence of positive hedonic signals (or pleasure). They include the synsets (a set of interchangeable synonyms) 'enthusiasm', 'gratitude', and 'humility'. We chose synsets describing positive hedonic signals that appeared to be the most statistically significant in explaining the project's success/failure. Later, as a robustness check, we construct the opposite variable: $emotions\_negative_i$. Negative emotional cues are calculated as the sum of words in the project that trigger negative emotional cues. These emotional cues are defined as emotional states characterized by the presence of negative hedonic signals (or pain). They include the synsets "fear", "anxiety", and "despair".

We assume that when the main text and founders' comments display more positive sentiments, the probability of success is greater, and this is also the case with a higher number of positive words. We treat these variables as affective behavioral factors because, in the conventional approach, investors may be influenced by the quality of the project or the risk taken, but should not be influenced by how the project is presented and by the additional determinants contained in the creator's comments. For more information on these three variables and how these variables were extracted, see the section *Text Analysis*.

[5] Valence is the affective quality referring to the intrinsic attractiveness (positive valence) or aversiveness (negative valence) of events, objects, or situations. The presence of positive valence by itself motivates action to effect that which the object of valence calls for, the presence of negative valence moves to escape or to achieve change (Frijda, 1986).

3. Methods and Data

3.1. Empirical Model Specification

The model using the above-mentioned variables can be written as follows:

$$Ln\left(\frac{P}{1-P}\right) = \alpha + \beta U_i^{'} + \gamma V_i^{'} + \delta W_i^{'} + \sum_{k=1}^{K} \theta_k category_{ki} + \sum_{l=1}^{L} \theta_l year_{li} + \varepsilon_i \qquad (1)$$

where P is the probability that the dependent variable equals one ($yi = 1$), which denotes a successfully financed project. A successfully financed project means that the project has received all the required financial funding before the project deadline.

The first vector of control variables $\boldsymbol{U}_i^{'}$ contains $\boldsymbol{U}_i^{'}$ = (*log_goal*$_i$, *duration*$_i$, *preparation*$_i$, *avg_pledge_opt*$_i$, *num_pledge_opt*$_i$, *images*$_i$, *media*$_i$, *words_text*$_i$, *words_blurb*$_i$, *delivery_time*$_i$). This vector defines the variables that we treat as conventional factors.

The second vector of control variables $\boldsymbol{V}_i^{'}$ contains $\boldsymbol{V}_i^{'}$ = (*creator_capital*$_i$, *social_media*$_i$, *num_positive_comm_cont*$_i$, *num_negative_comm_cont*$_i$); this vector defines the social media factors. The third vector of control variables ($\boldsymbol{W}_i^{'}$) contains affective factors that are in domain of behavioral approach: $\boldsymbol{W}_i^{'}$ = (*sentiment_comm_creator*$_i$, *sentiment_text*$_i$, *emotions_positive*$_i$, *emotions_negative*$_i$). The terms *category*$_{ki}$ and *year*$_{li}$ are dummy (0, 1) control variables for every category j as described in Appendix A and for every year, respectively.

3.2. Data

We analyze cross-sectional data from the U.S., Australia, Canada, the U.K., and an aggregate of selected European countries, focusing on individual crowdfunding projects over the period from April 21, 2009, to July 7, 2017. Our dataset is relatively rich as we combine two datasets. First, we collected 222,800 crowdfunding projects from Kickstarter for the U.S., 4,736 projects for Australia, 9,215 projects for Canada, 22,823 for the U.K., and 8,256 for the aggregate of European countries. Second, we also utilize unique data extracted using a web scraper specifically designed to gather data from the Kickstarter server. For better clarity and comparability, we exclusively focus on projects completed by July 2017, whether successful or not.

Similar to Mollick (2014) and Skirnevskiy et al. (2017), we eliminated the most extreme values of fundraising goals, as they predominantly represented non-serious attempts to raise funds. We excluded projects with goals above 1 million

USD (845 projects) and projects below 100 USD (4,579 projects). The exclusion of these projects enables better statistical inference of estimates and allows us to compare our results with those in previous studies. Appendix C provides a summary of descriptive statistics for categories of crowdfunding projects.

3.3. Model Estimation Procedure

In our empirical analysis, we employ a logistic regression model and maximum likelihood (ML) estimation, as the dependent variable is measured with a dichotomous variable. We then compute average marginal effects to measure the significance of the determinants of successful crowdfunding. These marginal effects are nonlinear functions of the parameter estimates and the levels of the explanatory variables. We report robust standard errors, making the estimator robust to certain types of misspecification, as long as the observations are independent.

3.4. Text Analysis

A Kickstarter project page contains, among other things, several facts in text form: the project title, a blurb (a short promotional text), and a detailed project description, containing images, videos, hyperlinks, etc. Moreover, backers and the project founder can add comments, enabling the receipt of feedback and support. The texts, along with other data (e.g., information about project duration or pledges), were downloaded from the Kickstarter server and analyzed.

The texts were tokenized to determine the number of words in them. The tokenization process involved removing HTML tags and entities, punctuation (including brackets, apostrophes, dashes, quotation marks, periods, and exclamation marks), and splitting the text where white space occurred (Palmer, 2010). Counting the occurrences of the HTML code representing multimedia (figures, videos, audio) enabled us to obtain information about the presence of images and other media items.

Due to the absence of a labelled corpus usable for training a machine learning model to determine sentiment or emotional cues, we use a lexicon-based approach applicable to various domains. Two approaches can be applied to determine sentiment in various parts of the text: lexicon-based and machine learning. The lexicon-based approach relies on the availability of lexicons and sets of additional rules. Sentiment or emotion is determined by the occurrence of predefined words or expressions from the lexicon in the text (Cho et al., 2014; Taboada et al., 2011). All occurrences of significant words or expressions and their sentiment values are then aggregated. The conclusion might be, for example, that a document is positive in aggregate, that it contains both positive and negative parts, or that the sum of weights of all positive expressions is x, whereas the sum of weights of all negative expressions is y (Thelwall et al., 2010). To determine the overall sentiment in the text in terms of positive or negative impressions, we used the VADER algorithm (Hutto and Gilbert, 2014). The model achieves performance comparable to sophisticated machine learning methods that require an extensive set of training data. The output of the VADER algorithm is a number between –1 (negative) and 1 (positive).

Emotional categories in the text are discovered using the linguistic resource 'Wordnet Affect' (Strapparava and Valitutti, 2004). This lexicon-based approach achieves higher precision in emotion detection than machine learning methods (Strapparava and Mihalcea, 2008). The words in the lexicon were searched in the texts, and the number of occurrences was counted. The categories of the words found in the texts (e.g., humility or gratitude) were used to label the text from the perspective of emotion (i.e., the emotion is or is not present in the text). To cover different versions of the same word (e.g., different tenses of a verb), we applied stemming to both the text and the lexicon using Porter's algorithm (Porter, 1980).

4. Evidence on the Factors that Impact Success in Crowdfunding Financing

This section presents our empirical results for the factors that impact success in financing crowdfunding. As already noted, we divided these factors into three categories: conventional factors, social media factors, and affective factors. In our basic setting, the dependent variable is a conditional probability that an individual project was successfully financed. We describe the average marginal effects defined as a partial derivative of the event probability concerning the predictor of interest.

Table 1 reports the marginal effects of the variables on the probability of success for an individual project. All columns relate to the regression in equation (1). At this point, we consider only the U.S. projects. The first column (model m1) features the results of the basic specification with conventional factors. The second model (m2) includes social media factors, such as the creator's social media capital, and the third (m3) includes affective factors based on our text analysis. The last column (m4) features results of the most complex model with dummy controls for years and project categories.

The results are comparable across the four models and, hence, seem to be robust. The variable $avg\_pledge\_opt_i$ is the mean of pre-set financing options for backers, and the variable $words\_blurb_i$ is the number of words describing the project in the blurb. These variables are not statistically significant in some of our specifications; however, both are significant in the model (m4) with control dummies. Other variables seem to be consistent and significant in all specifications.

Table 1

Factors Impacting Success in Crowdfunding Financing, US Projects from April 2009 to July 2017

Dep. Variable	**Probability of project success**			
Regression	(m1)	(m2)	(m3)	(m4)
Method	ML	ML	ML	ML
Sample	full	full	full	full
log_goal	–0.1123*** (–145.755)	–0.1131*** (–147.595)	–0.1125*** (–147.025)	–0.1053*** (–134.629)
duration	–0.0023*** (–30.046)	–0.0023*** (–31.820)	–0.0022*** (–31.420)	–0.0028*** (–38.443)
preparation	0.0000*** (3.698)	0.0000*** (4.239)	0.0000*** (4.094)	0.0001*** (6.369)
avg_pledge_opt	–0.0000 (–0.251)	0.0000** (1.983)	0.0000*** (2.649)	–0.0000*** (–6.426)
num_pledge_opt	0.0278*** (99.464)	0.0219*** (77.978)	0.0211*** (75.851)	0.0187*** (67.319)
images	0.0062*** (39.585)	0.0041*** (26.468)	0.0041*** (26.296)	0.0075*** (41.403)
media	0.0196*** (14.591)	0.0142*** (11.173)	0.0134*** (10.607)	0.0072*** (5.984)
words_text	0.0001*** (31.336)	0.0001*** (23.264)	0.0000*** (9.058)	0.0000*** (15.349)
words_blurb	–0.0002 (–0.927)	0.0001 (0.584)	–0.0000 (–0.115)	–0.0008*** (–4.598)
delivery_time	–0.0002*** (–23.933)	–0.0002*** (–21.890)	–0.0002*** (–21.018)	–0.0001*** (–12.104)
creator_capital		0.0707*** (25.950)	0.0715*** (26.336)	0.0719*** (27.146)
social_media		0.0325*** (20.003)	0.0303*** (18.636)	0.0225*** (14.095)
num_positive_comm_cont		0.0374*** (54.152)	0.0357*** (49.882)	0.0348*** (51.014)
sentiment_comm_creator			0.0492*** (9.769)	0.0722*** (14.786)
sentiment_text			0.0151*** (6.368)	0.0125*** (5.466)
emotions_positive			0.0152*** (27.223)	0.0119*** (22.251)
time dummies	no	no	no	yes
category dummies	no	no	no	yes
No. obs	218,947	218,947	218,947	218,947

Note: The columns report estimated coefficients with the z-statistics in brackets. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.

Source: Kickstarter, own computation.

Most notably, the higher the goal the individual project seeks to obtain, the lower the probability of its funding success, i.e., if the financial goal of the project is twice as large (100% higher), the probability of success decreases by about eleven percentage points. The probability of success is also lowered by a longer financing period (*duration*$_i$), by a longer promised delivery time (*delivery_time*$_i$), and by the number of words in the blurb of the project, *words_blurb*$_i$ (in the last model). However, longer preparation (*preparation*$_i$), a higher number of pledge options (*num_pledge_opt*$_i$), and a higher number of images and other multimedia items in the project (*images*$_i$, *media*$_i$) increase the probability of success.

Social media factors such as the creator's capital and experience (*creator_capital*$_i$), the number of social networking sites that mention a particular project (*social_media*$_i$), and the number of positive comments (*num_positive_comm_cont*$_i$) also positively influence the chances of success (m2 to m4). The variable *num_positive_comm_cont*$_i$ shows that having more comments from contributors with a positive sentiment increases the project's chances of success.

As far as the affective factors representing the sentiment of economic agents are concerned (m3 and m4), all three variables have a significant and positive impact on the funding success. In contrast to *num_positive_comm_cont*$_i$, *sentiment_comm_creator*$_i$ measuring the sentiment embodied in the comments of the creator. The impact of contributors' comments is significantly lower than that of the comments of the creator, but the scales are not directly comparable. The former measures the number of positive comments, the latter measures the overall sentiment in the comments of the creator. In sum, behavioral factors (both social media and affective) seem to play an important role in financing throughout the Kickstarter crowdfunding platform in addition to conventional factors. This role is not marginal, as the impact of these determinants is even stronger than those of some conventional determinants. As such, these behavioral determinants derived from behavioral economics should be taken into account when a new crowdfunding project is proposed. In this context, we confirm our Hypothesis 1 that both social media and affective factors have an important impact on the success of crowdfunding financing.

5. Findings Extending the Analysis and Robustness Checks

5.1. Rolling Time Windows Regression

To provide our results with additional information, we perform a series of robustness tests. Each specification is based on our original model, equation (1). First, we divide our sample into sub-periods: 2009 – 2011, 2012 – 2014, and 2015 – 2017, and re-estimate our model. We attempt to determine whether social media and affective factors play the same role in Kickstarter's early days and later on.

Table 2 presents the important factors in successful financing across three-year periods. In addition to the regression (m4) in Table 1, these regressions use control measures for periods and specific crowdfunding categories. The results of our new regressions are generally consistent with those in Table 1. Generally, it is clear that the funding goal remains the most crucial conventional determinant of project funding success. However, its impact across the three time periods (from 2009 – 2001 to 2015 – 2017) is decreasing.

T a b l e 2

US Projects, Sub-Periods 2009 – 2011, 2012 – 2014, and 2015 – 2017

Dep. Variable	**Probability of project success**		
Regression	(m5)	(m6)	(m7)
Method	ML	ML	ML
Sample	2009 – 2011	2012 – 2014	2015 – 2017
log_goal	–0.1332*** (–57.097)	–0.0968*** (–96.424)	–0.0810*** (–86.813)
duration	–0.0021*** (–16.508)	–0.0032*** (–28.726)	–0.0028*** (–24.057)
preparation	0.0002*** (3.093)	0.0002*** (10.658)	0.0000*** (3.004)
avg_pledge_opt	–0.0000** (–2.525)	0.0000*** (6.281)	0.0000*** (7.916)
num_pledge_opt	0.0172*** (21.399)		0.0171*** (46.861)
images	0.0037*** (2.604)	0.0081*** (34.918)	0.0069*** (34.484)
media	0.0106*** (2.930)	0.0071*** (4.994)	0.0139*** (7.438)
words_text	0.0001*** (5.010)	0.0001*** (20.163)	0.0001*** (14.056)
words_blurb	–0.0000 (–0.032)	–0.0008*** (–3.330)	–0.0009*** (–3.588)
delivery_time	–0.0001*** (–2.792)	–0.0001*** (–12.276)	–0.0002*** (–15.494)
creator_capital	–0.0452*** (–5.465)	0.0763*** (21.451)	0.1056*** (30.751)
social_media	0.0034 (0.752)	0.0320*** (15.473)	0.0180*** (8.662)
num_positive_comm_cont	0.0790*** (36.813)	0.0300*** (44.362)	0.0311*** (26.602)
sentiment_comm_creator	0.0400*** (3.025)	0.0927*** (15.687)	0.0695*** (9.039)
sentiment_text	0.0091* (1.626)	0.0048 (1.550)	0.0147*** (4.909)
emotions_positive	0.0155*** (10.496)	0.0154*** (22.805)	0.0085*** (11.052)
time dummies	yes	yes	yes
category dummies	yes	yes	yes
No. obs	34,765	134,615	97,404

Notes: The variable $num\_pledge\_opt_i$ was excluded from the regression (m6) because it prevented the ML algorithm from converging. This is due to the complete or quasi-complete separation in a logistic regression which causes the ML estimate for this regression coefficient not to exist. The same applies to Table 3, second column. The columns report estimated coefficients with the z-statistics in brackets. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.

Source: Kickstarter, own computation.

Nevertheless, we also observe some interesting exceptions (particularly in m5). Our results show that social media factors, such as the creator's social media capital and experience, $creator\_capital_i$, and the number of social networking sites that refer to the particular project, $social\_media_i$, do not play the expected role in the period 2009 – 2011. Presumably, this is because the social environment and mutual social networks among project creators (founders) and contributors did not exist in the early stages of Kickstarter's existence (founded in 2009). Certainly, in addition to this, no history of successful and unsuccessful project founders existed as a measurable sign of the founder's experience. Social media ties began to emerge during first years of Kickstarter's existence and fully materialized in the following years. The role of $num\_positive\_comm\_cont_i$ was twice as large in the initial sub-period, 2009 – 2011, as in the following two periods, reflecting that contributors' positive comments partially outweighed the role of other social media factors in the initial period. In fact, the role of the number of positive comments by other contributors outweighed even the impact of sentiment in the comments of the creator. This is the only period when this occurred. Affective factors remain important and significant, particularly $sentiment\_comm\_creator_i$, which had the strongest influence on funding success in the sub-period 2012 – 2014. As such, we confirm Hypothesis 2 that the role of factors influencing crowdfunding success evolves over time. At this point, further research on the various time windows in crowdfunding financing would be beneficial.

However, a different type of data would be needed, preferably at the level of the contributors to the crowdfunding campaigns. It can reveal much about how social ties and the social environment are formed in the different stages of crowdfunding platform development.

5.2. Generalization of the Factors of Success

After evaluating the factors impacting crowdfunding financing success of U.S. projects, we examine the same factors for Australian, Canadian, U.K., and European projects funded on Kickstarter. We examine the situation in Europe and its projects, which is a summary of European projects funded in euros across several countries of the European Union.[6]

This analysis can provide more general insight and allow us to verify whether the relationships we propose are universally valid or valid only in geographically uniform regions. Analyzed countries recently experienced a rapid increase in

---

[6] European projects on the Kickstarter until 2017 were relatively infrequent, so there are few observations per each country. That is why we have grouped these countries together (Austria, Belgium, Germany, Spain, France, Ireland, Italy, Luxembourg and the Netherlands).

crowdfunding projects, as demonstrated by Barbi and Bigelli (2017), who suggest that regional differences matter, and, as different founders attract different contributors, the factors in campaign success can also differ. We therefore investigate the existence of potential regional differences in Kickstarter crowdfunding financing when the founder comes from a different country. We do not consider other countries due to the lack of data; usually, a country has dozens or hundreds of projects.

T a b l e 3

Factors of Success in Australia, Canada, the UK and Europe

Dep. Variable	**Probability of project success**			
Regression	(m8)	(m9)	(m10)	(m11)
Method	ML	ML	ML	ML
Sample	Australia (2013 – 2017)	Canada (2013 – 2017)	UK (2012 – 2017)	Europe (2014 – 2017)
log_goal	–0.0877*** (–20.457)	–0.0898*** (–27.537)	–0.1056*** (–45.369)	–0.0724*** (–21.802)
duration	–0.0015*** (–2.849)	–0.0025*** (–6.289)	–0.0020*** (–7.459)	–0.0019*** (–5.332)
preparation	0.0002*** (2.577)	0.0001** (2.082)	0.0002*** (4.145)	0.0001 (1.391)
avg_pledge_opt	–0.0001 (–0.176)	0.0001* (1.862)	–0.0001*** (–3.400)	–0.0001 (–1.540)
num_pledge_opt	0.0178*** (11.415)		0.0168*** (21.033)	0.0135*** (15.316)
images	0.0068*** (7.547)	0.0103*** (15.359)	0.0059*** (14.288)	0.0058*** (15.054)
media	0.0150 (1.608)	0.0173*** (3.211)	0.0040 (1.219)	0.0109*** (2.957)
words_text	0.0001 (1.596)	0.0001*** (5.289)	0.0001*** (9.467)	0.0001*** (8.268)
words_blurb	–0.0003 (–0.292)	–0.0018** (–1.996)	–0.0002 (–0.386)	–0.0003 (–0.403)
delivery_time	–0.0003*** (–4.776)	–0.0002*** (–4.314)	–0.0003*** (–10.145)	–0.0003*** (–6.361)
creator_capital	0.0507*** (2.837)	0.0744*** (5.244)	0.0531*** (6.263)	0.0788*** (5.294)
social_media	0.0354*** (3.999)	0.0295*** (4.340)	0.0184*** (4.383)	0.0216*** (4.134)
num_positive_comm_cont	0.0152*** (6.271)	0.0213*** (9.181)	0.0241*** (15.117)	0.1222*** (9.438)
sentiment_comm_creator	0.0594** (2.072)	0.0763*** (3.503)	0.0588*** (3.869)	0.0594*** (2.829)
sentiment_text	0.0385*** (2.655)	–0.0097 (–0.885)	0.0047 (0.656)	0.0093 (1.283)
emotions_positive	0.0094** (2.535)	0.0118*** (4.640)	0.0090*** (5.632)	0.0033* (1.658)
time dummies	yes	yes	yes	yes
category dummies	yes	yes	yes	yes
No. obs	4,602	8,921	22,059	8,256

Note: The columns report estimated coefficients with the z-statistics in brackets. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively.

Source: Kickstarter, own computation.

Table 3 shows that the factors for success in crowdfunding campaigns in Australia, Canada, the U.K., and Europe do not substantially differ from those of U.S. campaigns. These results confirm Hypothesis 3 that there are not significant regional differences concerning factors of crowdfunding financing. The results are consistent with our previous assumptions, and they are, therefore, robust. Some of the explanatory variables for Australia are statistically insignificant, i.e., the effect on project success is not proven. This applies particularly to variables that measure the overall quality and appearance of a project, such as $media_i$, $words\_text_i$, and $words\_blurb_i$. In most countries examined, however, the variables of interest (all social media and affective factors, with a few exceptions) remain important factors in the success/failure of crowdfunding financing. As such, we can apply our conclusions to other developed economies, as the developed countries in our sample do not have any noteworthy regional differences in the determinants of Kickstarter project success.

5.3. Other Robustness Checks

5.3.1. Increasing the Creator's Social Media Capital and Experience

As previously mentioned, project creators on Kickstarter are not limited to a single project during their fundraising process. In fact, some creators have launched dozens of projects so far. Throughout the funding process, creators not only gain valuable experience but also attract a group of fans and potential future backers, which we refer to as social media capital. The variable $creator\_capital2_i$ is assigned a value based on the number of previously financed projects (e.g., two in the case of the third project of an individual founder), helping to explain a creator's increasing experience.

The first column (m12) in Table 4 presents the results of the regression in which $creator\_capital2_i$ is substituted for $creator\_capital_i$.[7] While these two variables are not directly comparable due to their differing scales, the substitution still offers additional insight. Each additional previous project by the same founder increases the chances of success for the next project by nearly two percentage points. Although this may not seem particularly high, it can play a significant role if founders have, for instance, more than ten previous projects. In this regard, we confirm Hypothesis 3, stating that social media capital and the past experience of project founders indeed impact the success of crowdfunding campaigns.

[7] Although we estimated the full model with equation (3), we show only the results for social media and affective factors. The remaining results do not substantially differ from our basic specification and are available upon request.

T a b l e 4

Additional Robustness Checks, US Projects from April 2009 to July 2017

Dep. Variable	**Probability of project success**			
Regression	(m12)	(m13)	(m14)	(m15)
Method	ML	ML	ML	ML
Sample	full	full	avg_pledge_opt<25	avg_pledge_opt>1006.9
creator_capital2	0.0174*** (8.971)			
creator_capital		0.0743*** (28.226)	0.0423*** (6.867)	0.0446*** (5.141)
social_media	0.0230*** (14.389)	0.0217*** (13.667)	0.0177*** (3.049)	0.0232*** (6.155)
num_positive_comm_cont	0.0349*** (51.172)	0.0444*** (60.948)	0.0538*** (13.940)	0.0340*** (27.303)
num_negative_comm_cont		–0.1035*** (–32.326)	–0.0497*** (–4.682)	–0.1059*** (–13.946)
sentiment_comm_creator	0.0718*** (14.727)	0.0729*** (14.962)	0.0491*** (3.117)	0.0632*** (4.930)
sentiment_text	0.0128*** (5.568)	0.0118*** (5.124)	0.0094* (1.643)	0.0163** (2.277)
emotions_positive	0.0118*** (22.102)	0.0112*** (21.290)	0.0082*** (4.499)	0.0037*** (2.745)
emotions_negative		–0.0061*** (–9.323)	–0.0030 (–1.252)	–0.0076*** (–4.257)
time dummies	yes	yes	yes	yes
category dummies	yes	yes	yes	yes
No. obs	218,947	218,947	21,713	22,985

Note: The columns report estimated coefficients with the z-statistics in brackets. ***, **, and * denote significance at the 99%, 95%, and 90% levels, respectively. The table only reports the coefficients of greatest interest; the estimates of the controls in $\boldsymbol{U}_i^{'}$ are available upon request.

Source: Kickstarter, own computation.

5.3.2. Negative Emotional Cues and Negative Comments

The second column (m13) in Table 4 contains additional variables measuring negative comments, *negative_comm*$_i$, and negative emotional cues, *emotions_ negative*$_i$. The remaining columns show regressions for projects with relatively small average pledge options (m14) and relatively large average pledge options (m15). The results reveal that negative emotional cues can significantly decrease the probability of funding success. Negative comments also strongly decrease the chances of success, as a single negative comment decreases the probability of success by more than 10%. In our model, negative comments seemingly possess much greater explanatory power than positive comments. This reflects the fact that contributors take external negative comments on the project more seriously than positive comments, and one negative comment can influence their behavior much more than one positive comment. Negative emotional cues have a weaker impact than positive emotional cues, meaning that positive hedonic signals contained in the text of projects are probably more important for funding success than the absence of negative ones. As such, we confirm Hypothesis 5 that sentiment and emotional cues in the project text description increase the success of crowdfunding financing.

Additionally, Appendix D shows the impact of negative comments on the proportion of projects (percentage of all projects with a certain characteristic) that, at the deadline, end with a specific percentage funded. Negative comments by backers can cause projects to fail even when a substantial portion of the goal is already met. This contrasts with Mollick (2014), who claims that backers are usually reluctant to contribute at the beginning of the contribution period, as they are not confident about the positive outcome of the action and they consider potential opportunity costs. As we see, social media factors (negative comments) can change this apparent regularity.

It is also worth mentioning that both negative and positive comments can be reflections of inherent quality of the campaigns in addition to being drivers or influencers of campaign success. In our regression, however, we check for other aspects of project quality, and thus the effect of negative and positive comments could largely be their net effect (regardless of the inherent quality of the project). Admittedly, the relationship between product quality, campaign success, and project comments is complex and still deserves further research.

5.3.3. The Role of Amount of Money Pledged

A common criticism of behavioral economics is often based on the argument that irrational behavioral motives tend to dominate when players wager smaller amounts of money (see, e.g., Levitt and List, 2007; Camerer et al., 2004). In typical economic experiments, stakes and decision-making costs are quite low for participants. However, in the real world, consequences and costs of decisions are often higher. This debate is crucial since fundamental economic predictions are centered on how people respond to changes in incentives, and the size of incentives clearly matters. Some empirical literature shows that respondents do not significantly change their behavior as the stakes increase (see stakes-sensitivity tests in the canonical bargaining game by Slonim and Roth, 1998; Cameron, 1999). We address this issue by examining the margins of our sample. Appendix E describes the main percentiles of our sample that divide the sorted data according to the explanatory variable $avg\_pledge\_opt_i$, which measures the mean of pre-set financing options for backers (in U.S. dollars).

We focus on differences between low pledges (when backers contribute small sums) and high pledges (when backers contribute large sums) to verify whether social media and affective factors play distinct roles in each case. The third column in Table 4 (m14) contains the sample in which the average pledge options are in the first decile of the sorted data (average pledges are 25.33 USD or less, i.e., the smallest pledges). The fourth column (m15) in Table 4 features the opposite, the last decile of the sorted data (projects with average pledges equal to or greater than 1,046.11 USD, i.e., the largest pledges).

We find that behavioral determinants of project success remain statistically significant across both subsamples. The impact of the number of negative comments is over twice as large for large pledges compared to low pledges. Also, negative emotional cues subtly embedded in project descriptions matter only for large pledges, not for small ones. However, we do not find any other consistent differences across our two samples. Social media and affective factors do not play a consistently more significant role in projects with lower average pledges; quite the opposite. Thus, we cannot confirm that contributors are more influenced by the social environment in the case of lower pledges.

Conclusions

To contribute to the debate on behavioral factors of successful crowdfunding campaigns, we used a rich dataset consisting of selected characteristics and information on individual crowdfunding projects. Our dataset encompasses 267,830 Kickstarter crowdfunding projects from April 2009 to July 2017 across the U.S., Australia, Canada, the U.K., and Europe. Additionally, we incorporated unique data extracted using a web scraper, specifically designed to extract data from the Kickstarter server.

First, we demonstrate that both social media and affective factors are significant and that we can even predict the direction of their impact. A more vibrant social environment, represented by the number of social sites mentioning the project, previous experience, and social media capital accumulated during prior campaigns, along with the number of positive/negative comments significantly influence the chances of success in a crowdfunding campaign. Our novel finding is that negative comments from other contributors matter much more than positive comments, significantly lowering the success rate of crowdfunding campaigns. A larger number of negative comments can even result in the failure of projects that have otherwise been successful in attracting sufficient funding. Regarding affective factors, we demonstrate that creator of a project can subliminally affect contributors by carefully crafting the project description and making comments during project discussions. By choosing words with positive markers (enthusiasm, gratitude, and humility), creators can increase the probability of success. However, using expressions with negative hedonic signals (fear, anxiety, and despair) can severely compromise their project, ultimately leading to failure in obtaining funds. The affective heuristic is a relatively new concept in behavioral economics, and we concisely show its importance not only in laboratory experiments but also in the field.

It is worth mentioning that both social media factors and affective factors investigated in our paper largely align with the standard framework and can be accounted for without adjustments in empirical models. For instance, social preferences (or social media factors) can be accommodated by simply adding another argument to a standard utility function (see, e.g., Angner, 2016).

Second, we contribute to the crowdfunding literature by showing that a social environment and social ties between creators and contributors require time to develop. We reveal that during the first two years of Kickstarter's existence, some social media factors did not substantially affect crowdfunding campaign success. In the absence of these factors, a number of positive comments by other contributors served as a decision-making guide. We also refute the notion that success factors differ across the U.S. and other developed countries (Australia, Canada, the U.K., and Europe). Our attempt to distinguish projects requiring higher pledges from those with lower pledges is also innovative. We show that there is no consistent difference between projects based on the size of the pledge required.

Third, we focused on the textual characteristics of a Kickstarter project's description and incorporated the method of text analysis into the financial strand of empirical literature. Financial studies rarely use text analytic techniques, which provided us with new insights into the role of the length of the project's description and the role of subliminal factors, which can alter the reader's initial impression and influence their judgment. A lengthier text description marginally increases the chances of project success, while a longer blurb has the opposite effect.

Our paper offers two general implications. First, our analysis of social media and affective determinants points to unconventional factors in successful crowdfunding campaigns, showing that they are both relevant and significant, and can substantially change the choices people make. We confirm that this insight applies not only in laboratory experiments but also in actual investments in crowdfunding campaigns and projects.

Second, our findings offer practical guidance for potential crowdfunding campaign creators who want to succeed. Our results illustrate factors that can lead to a higher probability of a successful campaign, including communication on social sites mentioning the project, previous founder's experience and social media capital gained during previous campaigns, positive comments on the project, and positive emotional cues contained in the project description. We also identify factors that substantially lower the probability of success, such as negative comments and negative emotional cues in the project description. Therefore, each funder should focus on marketing their campaign on social networks and offer funders an attractive story evoking positive emotional cues.

Unsuccessful crowdfunding campaigns result in a significant loss of money, energy, and time for creators and potential contributors who fail to receive their reward. We believe that our paper, along with the growing empirical literature in this area, can raise the success rate of crowdfunding campaigns and help crowdfunding creators and contributors save considerable economic resources.

References

AGRAWAL, A. – CATALINI, C. – GOLDFARB, A. (2015): Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions. Journal of Economics and Management Strategy, *24*, No. 2, pp. 253 – 274.

ALEGRE, I. – MOLESKIS, M. (2016): Crowdfunding: A Review and Research Agenda. Electronic Journal. Available at: <https://doi.org/10.2139/ssrn.2900921>.

ANGNER, E. (2016): A Course in Behavioral Economics. 2nd ed. London: Macmillan Education Palgrave.

BARBI, M. – BIGELLI, M. (2017): Crowdfunding Practices in and Outside the US. Research in International Business and Finance, *42*, pp. 208 – 223.

BOURDIEU, P. (1986): The Forms of Capital. In: RICHARDSON, J. G. (ed.): Handbook of Theory and Research for the Sociology of Education. Westport: Greenwood, pp. 241 – 258.

BUTTICÈ, V. – COLOMBO, M. G. – WRIGHT, M. (2017): Serial Crowdfunding, Social Capital, and Project Success. Entrepreneurship Theory and Practice, *41*, No. 2, pp. 183 – 207.

CAMERER, C. – LOEWENSTEIN, G. – RABIN, M. (2004): Advances in Behavioral Economics. Princeton: Princeton University Press.

CAMERON, L. A. (1999): Raising the Stakes in the Ultimatum Game: Experimental Evidence from Indonesia. Economic Inquiry, *37*, No. 1, pp. 47 – 59.

CHO, H. – KIM, S. – LEE, J. – LEE, J. S. (2014): Data-driven Integration of Multiple Sentiment Dictionaries for Lexicon-Based Sentiment Classification of Product Reviews. Knowledge-Based Systems, *71*, pp. 61 – 71.

COLEMAN, J. S. (1988): Social Capital in the Creation of Human Capital. American Journal of Sociology, *58*, pp. 95 – 120.

COLOMBO, M. – FRANZONI, C. – ROSSI-LAMASTRA, C. (2015): Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. Entrepreneurship Theory and Practice, *39*, No. 1, pp. 75 – 100.

CORDOVA, A. – DOLCI, J. – GIANFRATE, G. (2015): The Determinants of Crowdfunding Success: Evidence from Technology Projects. Procedia – Social and Behavioral Sciences, *181*, No. 11, pp. 115 – 124.

CROSETTO, P. – REGNER, T. (2015): Crowdfunding: Determinants of Success and Funding Dynamics. [Grenoble Applied Economics Laboratory Working Paper 2015-02.]

DAMASIO, A. R. (1994): Descartes' Error: Emotion, Reason, and the Human Brain. New York: Putnam.

EPSTEIN, S. (1994): Integration of the Cognitive and the Psychodynamic Unconscious. American Psychologist, *49*, No. 8, pp. 709 – 724.

ETTER, V. – GROSSGLAUSER, M. – THIRAN, P. (2013): Launch Hard or Go Home! Predicting the Success of Kickstarter Campaigns. In: MUTHUKRISHNAN, M. and ABBADI, A. E. (ed.): Proceedings of the First ACM Conference on Online Social Networks, Boston, pp. 177 – 182.

FARRELL, A. M. – GOH, J. O. S. – WHITE, B. J. (2018): Financial Incentives Differentially Regulate Neural Processing of Positive and Negative Emotions during Value-Based Decision-Making. Frontiers in Human Neuroscience, *12*, pp. 1 – 11.

FINUCANE, M. – ALHAKAMI, A. – SLOVIC, P. – JOHNSON, S. (2000): The Affect Heuristic in Judgments of Risks and Benefits. Journal of Behavioral Decision Making, *13*, No. 1, pp. 1 – 17.

FRIJDA, N. H. (1986): The Emotions. Cambridge: Cambridge University Press. ISBN 978-0521316002.

HANSEN, P. G. (2016): The Definition of Nudge and Libertarian Paternalism: Does the Hand Fit the Glove? European Journal of Risk Regulation, *7*, pp. 155 – 174.

HENNIG-THURAU, T. – GWINNER, K. P. – WALSH, G. – GREMLER, D. D. (2004): Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet? Journal of Interactive Marketing, *18*, No. 1, pp. 38 – 52.

HUTTO, C. J. – GILBERT, E. (2014): VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. In: Eighth International AAAI Conference on Weblogs and Social Media, Ann Arbor, June 1 – 4.

JIANG, C. – HAN, R. – XU, Q. – LIU, Y. (2020): The impact of Soft Information Extracted from Descriptive Text on Crowdfunding Performance. Electronic Commerce Research and Applications, *43*, 101002.

KAUR, H. – GERA, J. (2017): Effect of Social Media Connectivity on Success of Crowdfunding Campaigns. Procedia Computer Science, *122*, pp. 767 – 774.

KOCH, J. – SIERING, M. (2015): Crowdfunding Success Factors: The Characteristics of Successfully Funded Projects on Crowdfunding Platforms. In: The 23rd European Conference on Information Systems (ECIS 2015): Proceedings, Munster, Germany.

KRAUS, S. – RICHTER, C. – BREM, A. – CHENG, C. F. – CHANG, M. L. (2016): Strategies for Reward-Based Crowdfunding Campaigns. Journal of Innovation and Knowledge, *1*, No. 1, pp. 13 – 23.

LARREA, de G. L. – ALTIN, M. – SINGH, D. (2019): Determinants of Success of Restaurant Crowdfunding. International Journal of Hospitality Management, *78*, pp. 150 – 158.

LEVITT, S. D. – LIST, J. A. (2007): What Do Laboratory Experiments Measuring Social Preferences Reveal about the Real World? Journal of Economic Perspectives, *21*, No. 2, pp. 153 – 174.

LIN, X. – SARKER, S. – FEATHERMAN, M. (2019): Users’ Psychological Perceptions of Information Sharing in the Context of Social Media: A Comprehensive Model. International Journal of Electronic Commerce, *23*, No. 4, pp. 453 – 491.

MOLLICK, E. (2014): The Dynamics of Crowdfunding: An Exploratory Study. Journal of Business Venturing, *29*, No. 1, pp. 1 – 16.

MOWRER, O. H. (1960): Learning Theory and the Symbolic Processes. Hoboken: John Wiley & Sons.

PALMER, D. D. (2010): Text Preprocessing. In: INDURKHYA, N. and DAMERAU, F. (ed.): Handbook of Natural Language Processing. Boca Raton: Chapman & Hall/CRC, pp. 9 – 30.

PARHANKANGAS, A. – RENKO, M. (2017): Linguistic Style and Crowdfunding Success among Social and Commercial Entrepreneurs. Journal of Business Venturing, *32*, No. 2, pp. 215 – 236.

PIGOU, A. C. (1920): The Economics of Welfare. New York: Palgrave Macmillan.

PORTER, M. F. (1980): An Algorithm for Suffix Stripping. Program, *14*, No. 3, pp. 130 – 137.

PORTES, A. (1998): Social Capital: Its Origin and Applications in Modern Sociology. Annual Review of Sociology, *24*, pp. 1 – 24.

RHUE, L. – CLARK, J. (2018): The Consequences of Authenticity: Quantifying Racial Signals and Their Effect on Crowdfunding Success. [SSRN Working Paper.]

RHUE, L. – ROBERT, L. P. (2018): Emotional Delivery in Pro-Social Crowdfunding Success. In: Proceedings of the 36th ACM Conference on Human Factors in Computing Systems, Montreal, Canada.

SIMON, H. A. (1957): Models of Man. New York: John Wiley.

SKIRNEVSKIY, V. – BENDIG, D. – BRETTEL, M. (2017): The Influence of Internal Social Capital on Serial Creators' Success in Crowdfunding. Entrepreneurship Theory and Practice, *41*, No. 2, pp. 209 – 236.

SLOMAN, S. (1996): The Empirical Case for Two Systems of Reasoning. Psychological Bulletin, *119*, pp. 3 – 22.

SLONIM, R. – ROTH, A. E. (1998): Learning in High Stakes Ultimatum Games: An Experiment in the Slovak Republic. Econometrica, *66*, No. 3, pp. 569 – 596.

SLOVIC, P. – FINUCANE, M. L. – PETERS, E. – MACGREGOR, D. G. (2007): The Affect Heuristic. European Journal of Operational Research, *177*, pp. 1333 – 1352.

STRAPPARAVA, C. – MIHALCEA, R. (2008): Learning to Identify Emotions in Text. In: Proceedings of the 2008 ACM Symposium on Applied Computing, Fortaleza, Ceara, Brazil.

STRAPPARAVA, C. – VALITUTTI, A. (2004): Wordnet-Affect: An Affective Extension of Wordnet. In: 4th International Conference on Language Resources and Evaluation, Lisbon, Portugal.

TABOADA, M. – BROOKE, J. – TOFILOSKI, M. – VOLL, K. – STEDE, M. (2011): Lexicon-Based Methods for Sentiment Analysis. Computational Linguistics, *37*, No. 2, pp. 267 – 307.

THALER, R. H. – SUNSTEIN, C. R. (2008): Nudge: Improving Decisions about Health, Wealth, and Happiness. New Haven/London: Yale University Press.

THELWALL, M. – BUCKLEY, K. – PALTOGLOU, D. – CAI, D. – KAPPAS, A. (2010): Sentiment Strength Detection in Short Informal Text. Journal of the American Society for Information Science and Technology, *61*, No. 12, pp. 2544 – 2558.

TVERSKY, A. – KAHNEMAN, D. (1974): Judgment under Uncertainty: Heuristics and Biases. Science, *185*, No. 4157, pp. 1124 – 1131.

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*, pp. 106 – 117.

YUAN, H. – LAU RYK – XU, W. (2016): The Determinants of Crowdfunding Success: A Semantic Text Analytics Approach. Decision Support Systems, *91*, pp. 67 – 76.

ZAJONC, R. (1980): Feeling and Thinking: Preferences Need No Inferences. American Psychologist, *35*, No. 2, pp. 151 – 175.

ZHENG, H. – LI, D. – WU, J. – XU, Y. (2014): The Role of Multidimensional Social Capital in Crowdfunding: A Comparative Study in China and the US. Information & Management, *51*, No. 4, pp. 488 – 496.

ZHOU, M. – LU, B. – FAN, W. – WANG, G. A. (2018): Project Description and Crowdfunding Success: An Explanatory Study. Information Systems Frontiers, *20*, No. 2, pp. 259 – 274

A p p e n d i x A

Data Sources and Descriptions

	Variable	Units	Expected sign*	Description	Data provider
Conventional factors	log_goal	logarithm of dollar	negative	logarithm of the target amount of project *i*	web scraper extraction from the Kickstarter server
	duration	number of days	negative	the number of days for which project *i* accepts pledges	web scraper extraction from the Kickstarter server
	preparation	number of days	positive	the time which elapsed between the day when the founder started working on the project on Kickstarter and the day when the funding campaign was launched	web scraper extraction from the Kickstarter server
	avg_pledge_opt	dollar	negative	the mean of pre-set financing options for backers (each project can set up many reward levels requiring various pledges)	web scraper extraction from the Kickstarter server
	num_pledge_opt	number of options	positive	the number of pledging options for backers	web scraper extraction from the Kickstarter server
	images	number of images	positive	the number of images describing the project on Kickstarter	web scraper extraction from the Kickstarter server
	media	number of multimedia	positive	the number of other multimedia elements such as audio, video, etc.	web scraper extraction from the Kickstarter server
	words_text	number of words	positive	the number of words describing the project in the main text	web scraper extraction from the Kickstarter server
	words_blurb	number of words	positive	the number of words describing the project in the blurb	web scraper extraction from the Kickstarter server
	delivery_time	number of days	negative	the number of days the project founder commits to delivering promised goods or services	web scraper extraction from the Kickstarter server
Social media factors	creator_capital	dummy	positive	the variable takes a value of one for founders with more than one earlier project on Kickstarter and zero otherwise	web scraper extraction from the Kickstarter server
	creator_capital2	number of projects	positive	the number of founders' projects financed before (e.g., two in the case of a third project of the particular founder)	web scraper extraction from the Kickstarter server
	social_media	number of http links	positive	the number of social networking sites mentioning a particular project	web scraper extraction from the Kickstarter server
	positive_comm	number of comments	positive	the number of positive comments made by contributors about the project	web scraper extraction from the Kickstarter server
	negative_comm	number of comments	negative	the number of negative comments made by contributors about the project	web scraper extraction from the Kickstarter server
Affective factors	sentiment_comm	value of sentiment	positive	the sentiment attributed to all creator comments (measured on a scale from –1 to 1)	web scraper extraction from the Kickstarter server; the VADER algorithm (Hutto and Gilbert, 2014)
	sentiment_text	value of sentiment	positive	the sentiment attributed to an individual project description (measured on a scale from –1 to 1)	web scraper extraction from the Kickstarter server; the VADER algorithm (Hutto and Gilbert, 2014)
	emotions_positive	number of words	positive	the number of words in the project description which trigger positive emotional cues	web scraper extraction from the Kickstarter server; the linguistic resource Wordnet Affect (Strapparava and Valitutti, 2004)
	emotions_negative	number of words	negative	the number of words in the project description which trigger negative emotional cues	web scraper extraction from the Kickstarter server; the linguistic resource Wordnet Affect (Strapparava and Valitutti, 2004)

Source: Kickstarter, own computation.

Appendix B

Correlation Matrix of Independent Variables

	log_goal	Duration	Preparation	avg_pledge_pos	num_pledge_pos	Images	Media	words_text	words_blurb	delivery_time	creator_capital	social_media	positive_comm_cont	sentiment_comm_creator	sentiment_text	emotions_positive
log_goal	1															
duration	0.171	1														
preparation	0.113	0.002	1													
avg_pledge_pos	0.422	0.086	0.044	1												
num_pledge_pos	0.226	0.004	0.105	0.199	1											
images	0.215	–0.045	0.138	0.035	0.379	1										
media	0.116	–0.008	0.06	0.071	0.166	0.222	1									
words_text	0.263	–0.021	0.118	0.134	0.395	0.531	0.231	1								
words_blurb	–0.008	0.037	–0.016	0.011	0.004	–0.056	–0.004	0.009	1							
delivery_time	0.262	0.003	0.053	0.145	0.05	0.076	0.062	0.119	–0.004	1						
creator_capital	–0.109	–0.068	0.004	–0.064	0.079	0.148	0.051	0.085	–0.046	0.002	1					
social_media	0.099	0.006	0.056	0.05	0.198	0.301	0.166	0.256	–0.009	0.033	0.037	1				
positive_comm_cont	0.139	0.006	0.057	0.062	0.264	0.239	0.109	0.243	–0.007	0.030	0.078	0.143	1			
sentiment_comm_creator	0.038	–0.005	0.031	0.001	0.122	0.135	0.033	0.121	–0.013	0.004	0.029	0.048	0.268	1		
sentiment_text	0.008	–0.007	0.012	0.008	0.033	0.029	0.015	0.042	–0.001	–0.012	–0.001	0.024	0.016	0.012	1	
emotions_positive	0.122	–0.019	0.071	0.07	0.275	0.296	0.153	0.541	0.026	0.033	0.046	0.189	0.169	0.083	0.041	1

Source: Kickstarter, own computation.

Appendix C

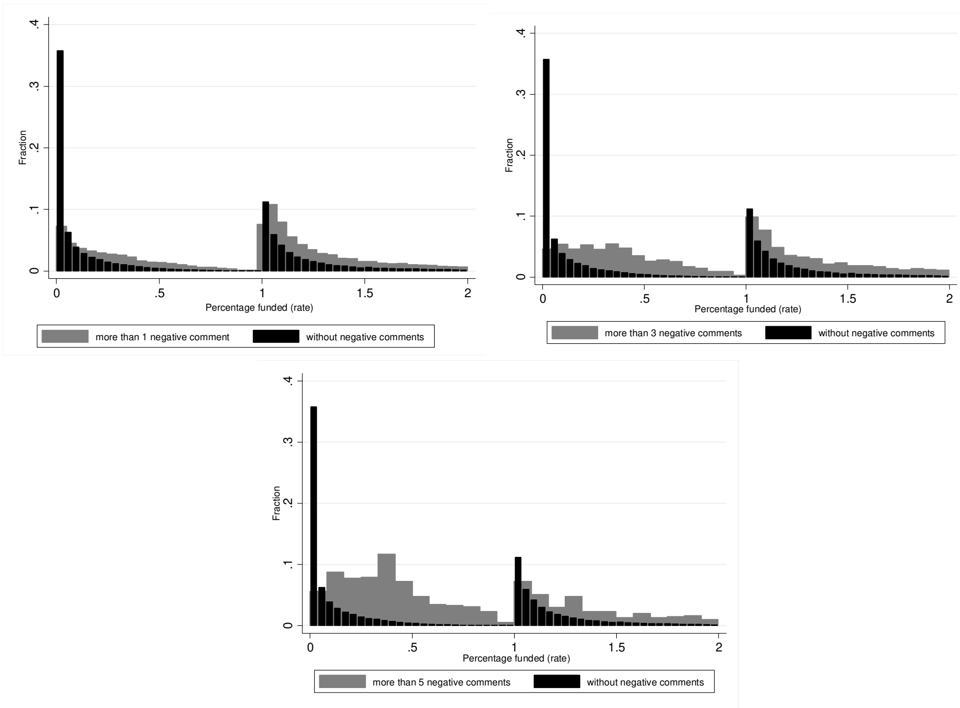
Descriptive Statistics of Categories of Crowdfunding Projects

	freq.	percent	successful	duration	preparation	num_pledge_opt	images	media	words_text	words_blurb	delivery_time
Art	24,849	9.760	0.422	32.506	32.395	7.549	4.212	0.116	437.946	19.310	88.528
Comics	8,094	3.180	0.580	34.465	55.232	11.879	10.222	0.115	646.651	20.025	118.594
Dance	3,145	1.240	0.666	32.886	29.706	6.668	1.369	0.132	419.186	19.369	69.350
Design	13,563	5.330	0.562	34.115	61.931	8.878	13.207	0.317	723.544	18.688	86.277
Fashion	14,713	5.780	0.293	32.749	46.484	7.680	8.531	0.115	460.570	18.655	75.147
Film/Video	47,003	18.470	0.452	35.243	35.623	8.772	3.067	0.366	554.632	19.997	135.956
Food	16,082	6.320	0.311	33.946	47.708	7.915	3.548	0.079	481.099	19.560	105.023
Games	19,164	7.530	0.492	32.353	56.076	9.694	14.226	0.682	963.872	19.447	153.600
Music	40,858	16.050	0.562	35.419	39.849	8.626	1.095	0.331	376.757	20.277	93.649
Photography	7,895	3.100	0.348	33.886	30.785	7.055	3.543	0.062	440.892	19.271	121.819
Publishing	31,681	12.450	0.349	33.944	40.350	7.192	2.789	0.094	565.724	20.107	128.679
Technology	18,430	7.240	0.262	35.090	52.544	6.933	7.986	0.347	698.586	19.279	116.472
Theatre	9,052	3.560	0.655	33.424	29.485	7.242	1.306	0.124	438.343	19.931	68.432
Total	254,529	100.000	0.442	34.167	42.315	8.222	5.069	0.260	549.810	19.689	111.215

Source: Kickstarter, own computation.

Appendix D

The Impact of the Number of Negative Comments on the Percentage Funded, US Projects from April 2009 to July 2017



Note: Projects with percentage funded <1 are failed projects, projects with percentage funded ≥1 are successful projects. We limited the percentage funded scale to (0, 2) for the sake of clarity; 2 on the scale means that the projects in this category are overfunded by two times. Some of the projects in our databases, however, reached more than ten times the goal amount.

Source: Kickstarter, own computation.

Appendix E

Percentiles of the Average Pledge Options, US Projects from April 2009 to July 2017

Percentile (%)	Average pledge option (USD)
1	5.00
5	17.50
10	25.33
25	57.50
50	165.29
75	424.09
90	1,046.11
95	1,580.83
99	2,512.14

Source: Kickstarter, own computation.