**Signalling Experience & Reciprocity to Temper Asymmetric Information in Crowdfunding**

**Evidence from 10,000 Projects**

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**Abstract**

Crowdfunding is a diffused *project* *finance* practice for funding early-stage projects by directly involving a large number of people by means of remote interaction through ICT-enabled platforms. Based on the original collection of empirical evidence from 10,000 Kickstarter crowdfunding projects, this paper develops a conceptual framework to understand and estimate the key predictors of success or failure for these funding campaigns. The main focus is on developing and testing specific hypotheses about the role that crowdfunding platforms play in facilitating the activity of signalling to mitigate the negative consequences of asymmetric information both in terms of moral hazard and adverse selection. The developed hypotheses were separated into two main categories, depending on whether signalling originated from the creator of the crowdfunding campaign, or the network supporting the crowdfunding project. Moreover, by providing an original longitudinal database, this paper emphasises the path-dependent nature of crowdfunding processes that together with additional proxies capturing social capital, reputation, patience and ambition, allows a significantly improved understanding and predictability of success or failure of these projects.

# 1*.* Introduction

Online Crowdfunding, the *alternative finance* practice of funding an innovation idea by directly involving a large number of people through an internet-mediated electronic platform and bypassing the traditional innovation funding institutions, has become a cornerstone of the early finance market, providing over 16.2 billion dollars of funding in 2014. As the crowdfunding market has grown, it has also diversified with an estimated 1250 crowdfunding platforms being considered active in 2014. By comparison in 2009, there were only an estimated 53 crowdfunding platforms and an estimated 530 million dollars of funding [(Massolutions, 2015)](#maskin), the amount of funds raised having increased by more than 3000 percent in six years. These funds provide key resources to the development of new technology and innovation usually supplying finance at a very early innovation stage, when traditional channels of innovation financing are often unachievable. This is often the case as many of the innovation projects benefiting from crowdfunding are from creators lacking a background of financial history and are often the victims of credit rationing due to asymmetric information ([Stiglitz and Weiss, 1981](#stig)). This paper will assess the main question of whether crowdfunding serves to bridge these information asymmetries by providing opportunities to develop signalling strategies ([Spence, 1974](#spence); [Ross, 1977](#ross)) through newly organized forms of credit exchanges taking place over ICT-enabled platforms [(Lehr and Sharafat, 2017](#lehr)). In this paper, we choose to focus on the adoption of signalling strategies to temper the adverse consequences of asymmetric information on access to innovation finance [(OECD, 2011)](#Oecd) as this approach based on the theory of strategic signalling and further detailed in the conceptual framework ([section 2.2](#_2_.2_Conceptual)) below and again in the literature review ([section 2.3](#_2.3_Literature_review)). This approach is particularly suited in providing a clear intuition for the metrics derived and built from the large database of primary data collected for this paper. In particular, this data can be interpreted as the different signals sent by the project creators and there supporting networks, as the evidence of a separating equilibrium ([Riley, 1979](#certo) ; [Cho and Kreps, 1987](#Cho)) in a strategic interaction environment characterised by a high degree of asymmetric information.

Within the data collected for this paper, many projects were funded to support innovations related to new technologies such as, for example, 3D printing, holographic lenses and the development of home robotics.[[2]](#footnote-2) The crowdfunding data analysed in this paper will be used to build a predictive tool, based on the role of the signalling opportunities provided to innovators and funders by the crowdfunding platforms, and aimed at better understanding the key factors for forecasting the sources of success and failure of different projects. The approach followed in this paper, should be of particular interest for innovation and entrepreneurship scholars as it also collects, explores and analyses data on *failed innovation projects*, which are of key relevance as often crowdfunding and entrepreneurship studies only focus on visible success stories.

This paper builds upon existing literature on the determinants of success and, critically, failure in online crowdfunding, extending current results by collecting and analysing a very rich longitudinal data set on crowdfunding that allows to consider some key inter-temporal factors in determining the potential success or failure of crowdfunding projects. The analysis is based on an extensive and up-to-date database of more than ten thousand projects, innovation ideas that have been seeking funding support through Kickstarter, a reward based crowdfunding ICT- platform, between the 14th of November 2015 and 6th of March 2016.

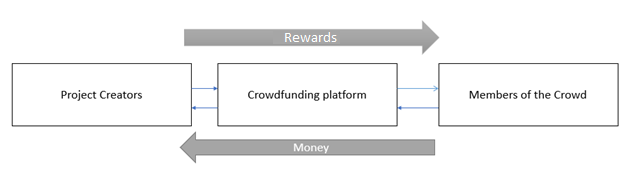


Figure 1 Summary of reward-based crowdfunding activity

The longitudinal nature of our primary data allows us to study the role of early *stage project backing* and the roles of impatience and ambition in predicting the probability of success or failure of these projects. Related research by [Schaer, Kourentzes and Fildes (2016)](#Scaher), focusing on the key early stages of the innovation process in the context of video games sales, modelled the early impact of Google Trends on market success. This contribution fits within the definition of innovation-related activities based on a lean development approach ([Cantamessa, 2016)](#cantamessa) in which a new product or service emerges out of a lengthy, iterative and interactive experimentation, in this paper’s framework, with the pre-product launch’s financing process.

The proposed model includes key proxies to capture the effects of *social capital*, *reciprocity* and *experience*, all considered as key signalling strategies aiming at reducing the usual barriers of access to credit for innovators posed by the pervasive presence of asymmetric information. These variables allow the paper to test different hypotheses about the effectiveness of these signalling strategies, while also helping to predict with increased accuracy whether a campaign would have failed or succeeded. In summary, this paper provides, not only relevant insights about the crucial area of innovation financing but also, useful tools for early-stage innovators in developing their own crowdfunding strategies.

After this introduction, in section 2, the paper discusses some of the relevant literature on crowdfunding and, based on this, it develops the conceptual framework and the main hypotheses to be tested. Section 3, on methodology, describes the data collection and introduces the econometric model utilised in the paper. Next, section 4 discusses the results obtained in relation to the research hypotheses. Finally, section 5 contains the conclusions.

# 2. Literature review, conceptual framework and hypotheses development

Early work on crowdfunding defined it as “a novel method for funding a variety of new ventures, allowing individual founders of for-profit, cultural, or social projects to request funding from many individuals, often in return for future products or equity.” [(Mollick 2014, page 1)](#Mollick)

Crowdfunding was classified into multiple sub-categories based on the backer (those funding the projects) participation rights [(Giudici et al, 2012](#giudici) and [Griffin, 2012)](#Griffin). Following [Colombo et al, (2015)](#Colombo) this paper will focus on the key factors leading to the success or failure of crowdfunding campaigns (see also [Kromidha and Robson, 2016](#Kromida), [Zheng et al, 2014](#Zheng) and [Hsiao, 2012).](#hsiao) This paper builds on, and extends, the findings developed in this literature, and others, outlined further in our literature review, to test a set of specific hypotheses, mainly derived from conjectures about the role of different signalling strategies, in a context of high information asymmetry between potential backers and innovators.

## 2.1 Reward-based crowdfunding

In this paper, the focus is on *reward-based* crowdfunding, *a category of* crowdfunding platforms, in which the backer is given a reward, based on the size of his donation which can be a product, artwork, or any reward they decide to give. ([Giudici et al, 2012](#giudici)). One additional key feature distinguishing different reward-based crowdfunding platforms is whether the platform is of an “*all or nothing”* or of a “*keep it all”* type. In the first case, the funding goal must be reached or no funds are received by the innovator, while in the second one, the *keep-it-all,* all the money raised is kept by the creators of the project regardless of whether the funding goal is reached or not [(Cumming et al, 2014)](#cumming). Kickstarter, the crowdfunding platform considered in this paper, uses an *all-or-nothing* approach.

The focus of this study is on *Kickstarter,* a reward-based crowdfunding ICT-enabled based platform that *has raised over 2.35 billion dollars and funded over 106.000 projects since its founding in 2008* [(Kickstarter Stats — Kickstarter, 2016)](#kickstarterstats). As such, Kickstarter has already become the focus of different research papers on reward-based crowdfunding (*[Mollick, 2014](#Mollick)*, [Kromidha and Robson, 2016,](#Kromida) [Kuppuswamy et al, 2015](#kuppuswamy)[*,* Lu et al., 2014](#Lu) and [Colombo et al., 2015)](#Colombo). This research identified key areas of interest in understanding the drivers of success or failure for crowdfunding campaigns launched on Kickstarter. Among these factors, the *number* and, more interestingly*,* the *distribution of backers[[3]](#footnote-3)* have been identified as crucial factors in predicting the success of a campaign *([Kuppuswamy et al, 2015](#kuppuswamy)).*

## 2.2 Conceptual framework

In this section, we discuss the conceptual framework required to develop a predictive tool that can be used to test different hypotheses about the key factors affecting the relative probabilities of success and failure of crowdfunding projects. In detail, we will focus on projects seeking financial resources through an ICT-enabled two-sided platform [(Lehr and Sharafat, 2017](#lehr)) facilitating linkages and signalling between innovators, on one side, to potential backers seeking project-related rewards, like prototypes, first editions, customized final product on the other ([Kromidha and Robson, 2016](#Kromida)).

The predictive tool that will be developed, will consider a set of key metrics, selected for their relevance in impacting success or failure of crowdfunding-based innovation projects. In this section, the relevance of these chosen metrics is also discussed and reviewed in relation to previous contributions to the field of crowdfunding, arising from the perspective of different disciplines such as innovation studies, entrepreneurship and economics ([Colombo et al, 2015)](#Colombo) ([Kromidha and Robson, 2016](#Kromida)) [(Mollick 2014, page 1)](#Mollick).

The main hypotheses will be developed, below, through the critical analysis of the key insights derived from the existing literature, with a specific focus on two aspects: the use of strategic signalling ([Spence, 1974](#spence); [Ross, 1977](#ross)) aimed at eliminating the barriers to access to finance due to the pervasive asymmetric information ([Stiglitz and Weiss, 1981)](#stig) and the path-dependent nature of the process ([David, 1985](#david); [Arthur, 1989](#arthur)) whereby the time profile of crowdfunding’s backing process will play a role, together with the time related entrepreneurial features such as ambition ([Levie and Autio, 2013)](#levie) and impatience ([Desai et al, 2010)](#Desai), in effecting the final outcome of an crowdfunding project. Once the main hypotheses are derived, the predictive tool will be built and used to test them against a large longitudinal dataset constructed and organized with primary data collected by the authors.

The insights gained from these tests will then be discussed in relation to our hypothesized effects, in order to derive a deeper understanding and the possible implications for innovators.

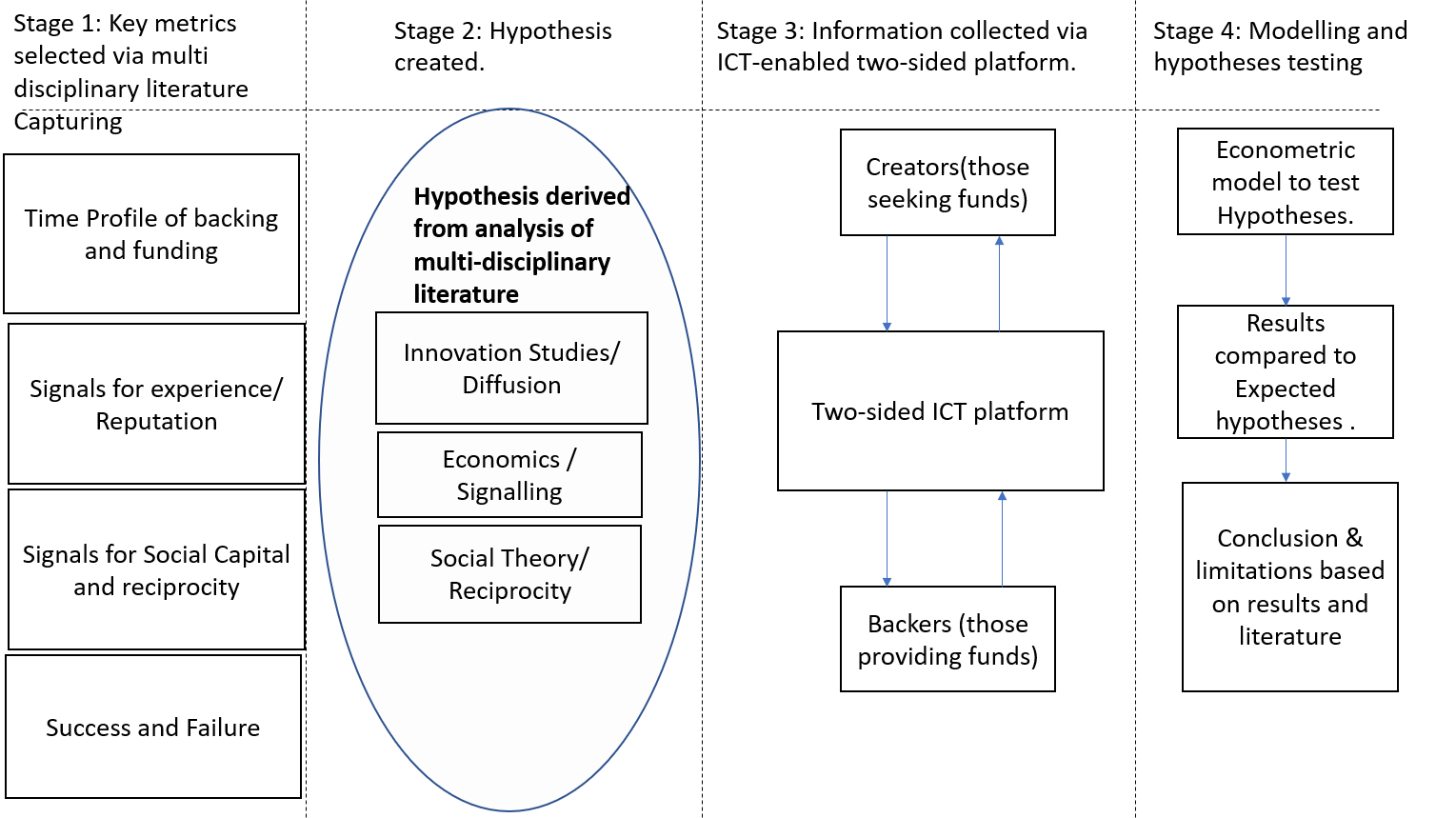


Figure 2 Research design framework

## 2.3 Literature review and hypotheses development

In this section, we derive the specific hypotheses, subsequently tested in the paper, in relation to the relevant literature and within the above described conceptual framework. We start by discussing the relevance of informational asymmetries in the credit markets and of signalling as a key strategy to overcome these informational barriers.

The hypotheses are separated into two main categories, hypotheses 1 to 3 focus on signalling by the creator of the crowdfunding campaign, while hypotheses 4 to 6 capture the impact of signalling by the network of people related to a crowdfunding project.

### 2.3.1 Asymmetric information and signalling

*Information asymmetry* between lenders and borrowers is a key feature of traditional credit markets, as exhaustively argued in [Gorton and Winton (2003)](#gorton) review. The increasing failure of credit markets to provide needed resources, in particular when these are to finance early stages of innovation projects characterized by high uncertainty [(OECD, 2011)](#Oecd), has been seen as the consequence of the pervasive presence of asymmetric information between funders and innovators. In fact, with credit market failures, no explicit lending rate can be defined to match supply and demand for credit, even when there would be a mutual willingness and reciprocal benefits to lend and to borrow. The seminal theoretical contribution deriving the conditions for such market failures can be traced back to the paper by [Stiglitz and Weiss (1981)](#stig) showing that credit rationing can be an equilibrium resulting from rational choices of lenders in the presence of asymmetric information. One of the key mechanisms through which asymmetric information disrupts credit markets has been identified in the presence of *adverse selection*, ([Akerlof, 1970](#Aker); [Rothschild and Stiglitz, 1976)](#Roth) a situation arising when the lenders are unable to distinguish the true quality of, and the risk associated with, a borrower. As a consequence of this asymmetric information, lenders will require higher lending rates that will only attract riskier projects, having a higher probability of failure and of not repaying the loans, and will not be accepted by less risky, more promising ones. Hence, only riskier projects *adversely select* themselves for credit applications, and rational lenders, aware about their ignorance in discriminating among projects but understanding the adverse selection consequences of the situation, will eventually be raising again their lending rates, further worsening the credit market conditions and weeding out the remaining intermediate-quality risk projects, leaving on the market, as potential borrowers, only the most risky ones, in a self-replicating process eventually leading to the collapse of the credit market. Focussing specifically on crowdfunding, our object of interest, [Belleflamme et al, (2013) and (2014](#Belleflameetal)) provide a comprehensive review of the impact of asymmetric information on crowdfunding from an economics perspective while [Ahlers et al, (2015](#Ahlers))’s literature review identifies asymmetric information as one of the major factors impacting on the success of crowdfunding from a entrepreneurship perspective.

This negative impact of information asymmetry between two parties can, however, be overcome if the better-informed party sends a signal about its quality to the less informed one as argued in early contributions in signalling theory ([Spence, 1974](#spence)[; Ross, 1977](#ross)), further developed in the review by [Sobel, (2009](#sobel)), from an economic perspective, and by [Connelly, Certo, Ireland, and Reutzel (2011),](#connelly) who review several contributions on signalling theory, from a management perspective identifying, for example, the symbolic role of “prestige” in signalling the quality of board structures ([Certo, 2003](#certo)).

This signalling literature shows that a necessary property for a signal to be valuable, in terms of reducing existing informational asymmetry, is that a signal has to be costlier for a sender of an, otherwise unobserved, lower quality. In this setting, it is possible to observe the emergence of *separating equilibria*, ([Riley, 1979](#certo); [Cho and Kreps, 1987](#Cho)) whereby the signals sent by different project creators are effectively revealing their underlying quality, thereby reducing or eliminating the initial information asymmetry and restoring the, otherwise missing, possibility of borrowing and lending.

In the context of crowdfunding projects such signalling strategies may serve to temper the adverse consequences of asymmetric information, by revealing key features about the underlying, otherwise unobserved, quality of a crowdfunding project. In this framework, [Kromidha and Robson (2016)](#Kromida) have assumed that both project creators (fundraisers) and backers (members of the crowd who support the campaign) can be signalling agents and, similarly, [Connelly, Certo, Ireland, and Reutzel (2011)](#certo) investigated the influence on a project success due to the interplay between signals originating from start-ups and those originating from third parties, while [Colombo et al, (2015)](#Colombo) argue that our specific crowdfunding platform of interest, Kickstarter, facilitates the success of a project by allowing signalling of reciprocity*,* measured via the number of other projects backed by a creator.

These signalling exchanges take place through ICT-enabled crowdfunding platforms, filling this innovation financing gap ([Giovannetti, 2017](#giovanetti2017)) through their ability in streamlining the signalling process, allowing information sharing back and forth between funder and proposers, in an easy, publicly verifiable, instantaneous way and bypassing the typical information asymmetries problems due to geographical distance ([Agrawal et al, 2015)](#Aker) through the web-based crowdfunding platform, wherever broadband internet access is available and affordable. Moreover, crowdfunding platforms not only allow the digital exchanges of information and signals, between backers and creators but, through their design, set of participation rules, users verification process, they also provide the soft governance ([Mollick 2014](#mollick)) for an otherwise completely decentralized process.

### 2.3.2 Developing Hypothesis 1, on experience as a strategic signal to reduce ex-post asymmetric information

Under asymmetric information, signalling can be used as a strategy to shape one’s *reputation* [(Kreps and Wilson, 1982)](#Kreps). Reputation can have different features depending on the type of image one wants to project. For example, a player might want to build the reputation of being a tough opponent prior to a confrontation, e.g. by choosing beer over quiche for breakfast ([Cho and Kreps, 1987](#Cho)), or to be a harsh punisher against an opponent’s deviations in a prisoner’s dilemma [(Maskin and Fudenberg, 1986](#maskin)). In our setting, however, a creator may want to increase its reputation for being a successful deliverer of projects since a positive reputation can be seen as “an important antecedent to online initial trust” ([Chen and Barnes, 2007](#chen)).

The strategy available to the creator to build a positive reputation and reinforce online trust is captured by signalling the experience she/he has in delivering completed projects. Trust building can be especially valuable in conditions of ex-post asymmetric information to respond to the risk of *moral hazard;* in fact, as identified in the Principal-Agent literature ([Jensen and Meckling, 1976](#jensen); [Townsend, 1979](#townsend)), *moral hazard* arises from post-contractual incomplete monitoring and informational asymmetry, whereby a principal is unable to fully observe the actions taken by its agent.

[Lin et al (2013)](#Lin) identified the costs of reputational loss, defined as *social stigma*, in online peer to peer finance and the relevance for borrowers to be able to send signals about it, in order to increase their funding success.

In crowdfunding, backers are clearly unable to perfectly observe the actual project creators at work beyond their self-representation through their project website on the Kickstarter’s platform. Hence creators, by signalling about their experience, may reduce the negative consequences of *moral hazard* by indicating objective evidence about their previous experience in delivering past projects.

This leads to the formulation of the first hypothesis:

***H1: Signalling about a project’s creator experience has a positive impact on the probability of the project’s success.***

The independent variable for the signalling of experience, used to test H1 is the number of previously launched projects by the same creator on the Kickstarter platform.

### 2.3.3 Developing Hypothesis 2 and 3, on entrepreneurial ambition and impatience

The finance literature has highlighted how optimism and confidence are key firms’ traits in securing funding ([Dai et al, 2017](#david)), while the risk of overconfidence has also been linked to an increased likelihood of their ventures failures [(Bernardo and Welch, 2001](#Belleflameetal)). The co-existence of both these effects of ambition on success and failure calls therefore for an empirical estimation of the role of ambition on a project’s success or failure, in the Kickstarter database.

Another common trait of start-ups is that of impatience, a feature also identified in [Aghion et al (2002)](#Aghion) as an aspect of Schumpeterian innovations through creative destruction ([Schumpeter, 1942](#schump)). The role of impatience in economics was identified by [Fisher (1930)](#Fisher) as the gratification in obtaining goods in the present rather than in the future, and it is seen as a fundamental attribute of both personal characteristics and expectations about future income streams, resulting from the interplay of both cognitive-behavioural and economic perspectives ([Thaler, 1997](#Thaler)). More recently, with a focus on technology forecasting, [Meade and Islam (2006)](#Meade) underlined the critical trade-off posed by impatience for innovators as “Optimal launch timing balances inventory costs against the possible loss of customers due to impatience.” [(Meade and Islam 2006, page 531](#Meade)), while [Desai et al (2010)](#Desai), using a model of asymmetric information and incomplete contracts, find that impatience can be an entrepreneurial response to the inability of accessing innovation finance, and that impatience increases the chances of innovation failure, or in these authors’ terms, it favours the emergence of *destructive entrepreneurship*, defined as wealth-destroying entrepreneurial activities. Such a destructive outcome can also be seen as resulting from the failure of long term cooperation, due to impatience, measured through high discount rates, that incentivise deviation from cooperative strategies, by rewarding short term gains against long term losses due to punishments for deviating from cooperation [(Maskin and Fudenberg 1986)](#maskin). The contributions lead to the following hypotheses:

***H2: A campaign’s project ambition has a positive and significant effect on its probability of success.***

The independent variable to test H2 is the stated funding objective of a project as a metric for ambition.

The role of patience of the *creator* is considered in the following hypothesis

***H3: A campaign’s project duration has a positive and significant effect on its probability of success***

The independent variable used to test H3 is the *stated duration of the campaign*, capturing the creators patience.

### 2.3.4 Developing Hypothesis 4, on reciprocity as a strategic signal to reduce ex-ante asymmetric information

As discussed above, signalling, to be valuable, has to be costlier for riskier projects than for less risky ones. In our case, risk can be measured in terms of likelihood of successful completion of an innovation project or, from a Kickstarter’s backer’s perspective, it implies the risk of not obtaining a viable or meaningful reward.

In the hypothesis presented below, we consider the public display of a creator’s activity in backing other creators’ projects as a strategic signal. Suppose the creator of project A backs a project B, this activity will be seen as a costly signal (of *reciprocity*) from the creator of project A, that also brings the rewards of the increased visibility, for project A, on the webpage of the supported project B, visible in particular to the creators and backers of project B and to other members of the crowd who visit project B’s webpage. The expenditure made to back other projects, from a resource-scarce creator looking for financial backing through crowdfunding, can, therefore, be seen as an investment in advertising expenditure. Indeed, by following the insights from social identity theory, the fact that project A appears as a backer of another project B could extend project A’s identity collective, ([Kromidha and Robson, 2016)](#Kromida) by also including into this collective the existing backers of project B.

However, as discussed above, for the creator’s activity of backing other projects, *reciprocity*, to be interpreted as a valuable signal in reducing the consequence of adverse selection also needs to be costlier for riskier projects.

*Reciprocity* has this characteristic, as the increased visibility, due to the backing of other projects, brings increased scrutiny and better assessment of a project quality and risk, and increased exposure will raise the probability that some of the newly acquired webpage visitors, could identify the project’s weakness and, through their own signalling/comments, they could deter other potential backers. Hence, advertising through reciprocity is less costly if your project, once more visible, reveals its underlying good quality.

Given this correlation between the cost of *reciprocity* and the riskiness of a project, signalling through reciprocity can be effective in reducing the consequences of asymmetric information. Hence, a crowdfunding platform by allowing the display of information about the number of backed projects, also provides a key tool for signalling and, overcomes the potentially fatal consequences of asymmetric information, facilitating the overall lending activities and the funding success of valuable innovations projects. This leads to the formulation of the fourth hypothesis,

***H4: Signalling reciprocity, by backing other projects, has a positive impact on the probability of a project success.***

The independent variable used to test H4 is the number of other backed projects by the creator of a crowdfunding campaign.

### 2.3.5 Developing Hypothesis 5, on external social capital

The OECD defines *social capital* as “networks together with shared norms, values and understandings that facilitate co-operation within or among groups” [(Keeley, 2007](#Keeley)). [Coleman, (1988)](#Colombo) decomposed this construct into three separate elements: the first being the obligations and expectations among the members of the network, the second being formed by the network’s information channels and, the third being the set of social norms keeping it together. These three elements “…all consist of some aspect of social structures, and they facilitate certain actions.” ([Coleman, 1988, page 98](#Colombo)). [Fafchamps and Minten (2002](#fafchamps)) defined the concept of *social network capital* as the social capital bringing relational advantages only due to information spreading throughout a network. For these authors, *social network capital* may even substitute for the presence of social trust and norms, typically underlying the benefits of traditional social capital [(Putnam, 1995)](#putman).

Online communities, built around social networks provide typical examples of these key characteristics of social network capital ([Ellison et al, 2007](#ellsion)). In the field of peer to peer finance, for example, [Lin et al (2013)](#Lin) identify the role of an external online network to strengthen the social capital of those seeking online peer to peer finance. These authors focus on the role played by *online friends* in improving the likelihood of success in obtaining credit. Moreover, similarly to our theoretical framework, these authors also offer new empirical evidence on the importance of signalling in peer to peer credit markets where agents face information asymmetry. In such environments, these authors show how the gathering of “soft” information through external online networks can become a critical element to successful lending outcomes.

*External Social networks* also play a key role, in shaping crowdfunding platforms governance, as the platforms not only provide direct links between backers and funders but also, indirectly, they link their respective external social networks, as a backer may advertise his backing of a project onto its own social network of connections and, similarly, a creator will utilise its social network friends to signal the strengths of their project and to attract additional backers to the crowdfunding project’s page.

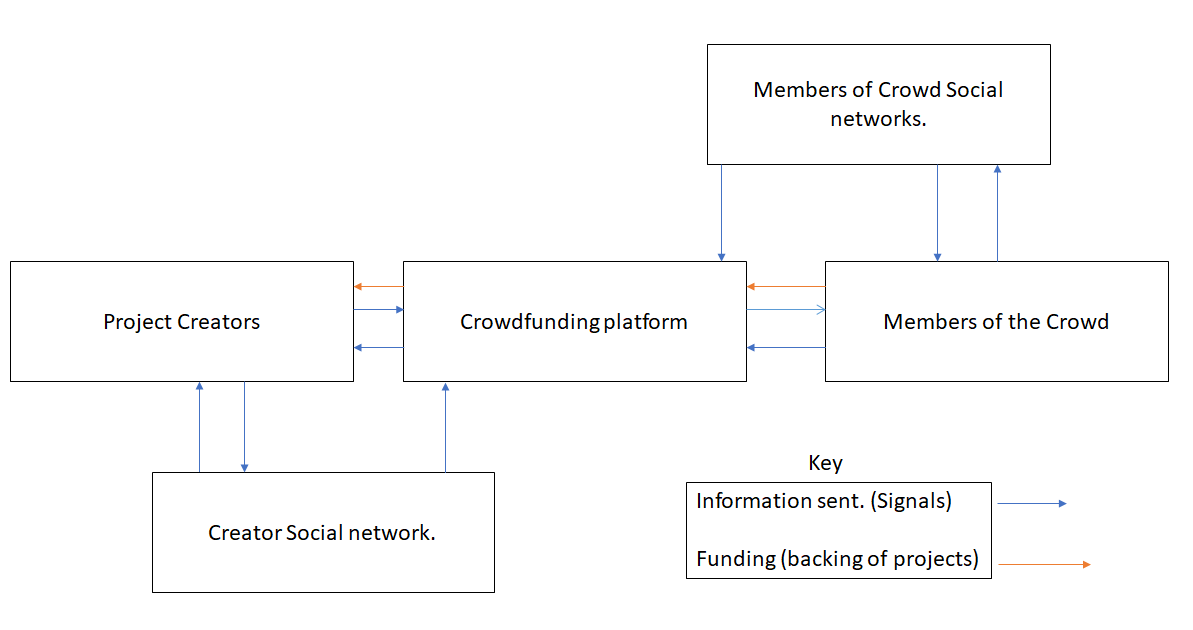


Figure 3 Structure of crowdfunding informational network

In the context of Kickstarter, [Colombo et al, (2015](#Colombo)) capture the construct of *external social capital* with the number of normalized *LinkedIn* connections of an individual project creator. Also focusing on Kickstarter, [Kromidha and Robson, (2016)](#Kromida) argue that the size of the network of online friends of a project’s creator is key for its success, especially as the efficiency of networks does not decrease when these become larger. As metrics for external social capital, these authors consider both: the logarithm of the number of friends the fundraiser has on its own Facebook page and the logarithm of the number of shares, i.e. when a visitor on the project website shares it on its own Facebook page during and after the fundraising period. The display of external social capital metrics on the Kickstarter project page provides an additional strategic signalling dimension, about the intrinsic project quality as measured by the size of its external social networks. However, [Colombo et al, (2015)](#Colombo) did not find a significant relationship between the number of LinkedIn connections and success on Kickstarter. Conversely, [Kromidha and Robson (2016)](#Kromida) found a weakly significant effect of the number of Facebook friends and shares, offering support to their hypothesis that social capital increases Kickstarter success.

The next hypothesis will also focus on the role of external social capital and its impact on project success:

***H5: A project’s external social capital has a positive impact on the probability of its success.***

The independent variable used to test H5, is the number of the project creator’s Facebook’s friends, as displayed (and signalled) on the crowdfunding platform.

### 2.3.6 Developing Hypothesis 6, on the role of early backing and funding

The *temporal profile* of a project funding is another key dimension in determining its success in crowdfunding. This notion is captured in the definition of *path-dependency* ([David, 1985](#david), [Arthur, 1989](#arthur)) stating that a sequence of minor events in the stochastic history of the adoption or diffusion of a given technology may exert an irreversible impact on the final outcome of its success and/or diffusion. Moreover, the timing of innovation processes includes a critical temporal window often defined as the *Valley of Death,* ([Branscomb and Auerswald, 2003](#Branscomb)[; Markham, 2002,](#mark) [Markham et al. 2010](#mark), [Giovannetti, 2017](#giovanetti2017)) describing the time profile of the resource gap arising before the commercialization phase, capturing the time period when start-ups need more investment and support, as there is otherwise a high risk of project failure.

By adopting a *path-dependency* perspective, the original longitudinal database collected in this paper, allows an evaluation of the specific impact of early events, e.g. the number of early backers, on the overall probability of success or failure of Kickstarter’s crowdfunding campaigns. Crowdfunding provides a unique approach as it enables people to act as start-ups without the requirements of large funds or complex technical knowledge, however, this, in itself, may be problematic as it might imply that backers are unable to fully assess the risks involved in crowdfunding. As early funders are exposed to limited information about key features of the sponsored innovation, the time profile of the arrival of a project’s backers might provide relevant information that can be decisive in bringing in further backers. Hence, the number of early backers might provide signals for potential success, kick-starting a process of self-fulfilling expectations. However, differently from those analysed in the previous hypotheses, these signals are non-strategic ones, as they are driven by some initial random arrivals of early backers, generating a self-reinforcing and *path-dependent* process driving the final number of backers eventually reached by the project.

In practice, early backers not only bring their funds to the project but also carry a positive signalling externality, fostering *herd behaviour* ([Banerjee, 1992](#baner) and [Bikhchandani and Sharma, 2000](#bikhchandani)). [Colombo et al., (2015)](#Colombo) chose to measure the early backing and cumulative funding of a campaign at the first 10 days of the standard 60-day campaign. This paper adopts these same metrics to estimate, for a significantly larger and more recent collection of projects, the effect of early backing on the final probability of a campaign’s success or failure. This allows the relevance of herd behaviour to be tested, as non-strategic signal in reducing informational ignorance about a new technology in the context of crowdfunding. This leads to the sixth hypothesis of the paper.

***H6: Early funding and early backing are critical factors in increasing the probability of a campaign’s success.***

The two independent variables adopted to test H6 are: 1) the number of backers each project reached by the first sixth of the duration of the campaign and 2) the amount of money raised in the first sixth of the duration of the campaign.

# 3 Methodology

## 3.1 Data collection

The data used in the analysis were collected from the Kickstarter’s platform between the 14th November 2015 and the 6th March 2016, capturing campaigns which were completed in this timeframe. The collection was performed by the authors using *Import.io,* a software which enables active websites crawling and transfer of the key desired information into the researchers’ databases. Similar data collection for the Kickstarter crowdfunding platform were performed by ([Mollick 2014](#mollick)), ([Colombo et al, 2015](#Colombo)) and ([Kromidha and Robson, 2016)](#Kromida). In detail, Mollick analysed 48,526 completed Kickstarter projects in the United States from its inception in 2009 to July, 2012. Colombo’s data collection included a sample of 669 Kickstarter projects posted since October 20, 2012 and closed by January 10, 2013 in the categories of design, technology, and video games. Their variables included projects duration, and information related to proponents, such as the number of Kickstarter projects that a proponent had backed at the time of launching her own crowdfunding and the number of connections that each individual proponent had on her LinkedIn profile. Finally, Kromidha collected records of the 5000 most funded projects in Kickstarter in April 2014, spanning multiple industries and countries. For each of these projects they also collected “the number of friends of the founders on Facebook. ….the number of shares by backers of the project on personal Facebook pages, …the number of comments exchanged between backers and the fundraiser and the number of updates which have been posted by the fundraiser” ([Kromidha and Robson, 2016, page 615)](#Kromida).

Each day, up to 20 newly launched crowd-funded projects’ campaigns, from each of the 15 different categories, discussed below, were collected, providing a maximum of 300 projects per day.

The graphs in Figure 4 below display the daily frequencies of when projects were created.

Figure 4 Projects each day of the collection period

Differently from previous contributions, the longitudinal nature of the database allows us to represent the time profile of the number of backers and the amount of funds, as displayed for example in two specific projects on an *Affordable weather transformer* and on an electrical certification map in Figure 5 below. Data for each project was recorded every single day, until the projects’ campaign ended, thus capturing the full funding pattern of the project from its launch to its end.

Figure 5 backers per day across two sample campaigns of the Kickstarter dataset.

The key metrics, used in the construction of the model, were collected through *import.io* for each of these projects at the beginning of the campaign as described in [Table 1](#table1), below. In choosing a metric to represent a successful Kickstarter campaign, one must consider that there are four possible outcomes of a Kickstarter campaign. Firstly, the campaign can *succeed*, this is when the funds raised are greater than the initially stated funding goal; in this event, the project’s creator receives all the funds. The second possible campaign’s outcome is *failure*; this happens when the initially stated funding goal is not reached by the end of the campaign (with a maximum limit of 60 days for the campaign). The third possible outcome is a *cancelled* campaign; this happens when the creator of the campaign cancels the campaign before it has reached the end of its planned duration. The fourth possible outcome is *suspension*, this is observed when the Kickstarter’s platform, decides to suspend the crowdfunding campaign. This can be due to the campaign being seen as fraudulent, or breaking copyright agreements.

Both *cancelled* and *failed* campaigns, when observed during the data collection period, have been considered as constituting failure to reach the stated funding goal [Mollick (2014)](#Mollick). However, suspended campaigns have, on the contrary, not been considered as failures as one was unable to discern if a suspended campaign would have succeeded or not prior to its suspension. Thus, the successful campaigns are all campaigns which have reached their stated funding goal by the end of the campaign’s duration while the failures are all campaigns which did not reach their goal or were cancelled.

The independent variables: *early funding* and *early backing* introduced to capture the *path-dependent* nature of the crowdfunding projects, discussed in Hypothesis 6, were measured as the amount of funds and the number of backers, each project reached by the first sixth of the duration of the project (Colombo et al, 2015). As such, for a 60-day project, the number of backings and amount of funds reached by the 10th day of the campaign was recorded as early backers and funds. Finally, while collecting the data for the Kickstarter categories, similar categories were combined, in order to avoid multicollinearity. The categories’ recombination is shown in ([Table 1](#table1)) below.

## 3.2 The Model

Based on the collected projects’ dataset, this section addresses the main hypotheses introduced in section 2.3, by introducing a logit regression to estimate the effects of the relevant predictors on the probability that an innovation project successfully raises enough funds to reach its funding goal. The dependent variable (success or failure) is a binary dummy variable, assuming value one if the project has reached its funding goal or zero, if the project failed to do so. The full list of variables utilized in the model identification is provided in [Table 1](#table1)[[4]](#footnote-4), below.

**Table 1**

Variable names and descriptions

|  |  |
| --- | --- |
| Variable name | Variable description |
| Success or failure | Dependent variable. 1 if funding succeeds. 0 if funding fails. |
| Previously created campaigns | Number of previous campaigns on Kickstarter the creator of the campaign has run. |
| Previously backed campaigns | Amount of projects the creator has backed within Kickstarter. |
| Funding goal | The amount of funds that the campaign must reach to be successfully funded. |
| Duration | The length of the campaign in days. |
| Earlyfunds | Funds raised by the campaign in first 1/6th of its duration. |
| Earlybackers | Backers raised by the campaign in first 1/6th of its duration. |
| Facebook connections | Facebook friends connected to Kickstarter project. |
| Usa | Projects based in the United States of America. |
| Europe | Projects based within the continent of Europe. |
| Asia | Project based within the continent of Asia. |
| Africa | Projects based within the continent of Africa. |
| Arts & Craft | Combination of the dummy variables for art and craft. |
| Comics & Journals | Combination of the dummy variables for comics publications and journalism. |
| Technology and games | Combination of the dummy variables for technology and games. |
| Theater Dance & Music | Combination of the dummy variables for theatre dance and music. |
| Fashion & Design | Combination of the dummy variables for fashion and design. |
| Photo & film | Combination of the dummy variables for photo and film. |

A preliminary analysis of the outliers in the data set led to the removal of all the projects which had funding goal of above the $100,000 threshold, as there were examples of projects which raised 0 dollars and yet had a 100-million-dollar funding goal. Secondly, any campaign that raised over $5000 by the first 1/6 of its duration was also removed from the dataset as these were incredibly and immediately successful projects and were removed in order to explain as much of the success and failure as possible by focusing on the normal duration campaigns. This outlier removal process left a database with 9652 campaigns, used in the estimation of the first model.

For the resulting dataset, three different models specifications were estimated, by progressively including quadratic values for three of the explanatory variables. These were the number Facebook Connections, the Duration of the Campaign and the Funding goal. The estimation results for the main model are reported, in [Table 2](#table2). With the remaining model specifications reported in the Appendix ([Table 4](#table4)), for completeness and robustness.

**Table 2** Estimation results

Binary Dependent variable: Project’s success or failure

|  |  |
| --- | --- |
| Independent Variables | Model |
| Previously created campaigns | 0.149540\*\*\*  (0.0198717) |
| Previous backed campaigns | 0.008058\*\*  (0.0025193) |
|  |  |
| Funding goal | -0.000267\*\*\*  (9.63E-06) |
| Duration | -0.016546\*\*\*  (0.00302) |
| Early-funds | 0.001992\*\*\*  (0.0000855) |
| Early-backers | 0.028672\*\*\*  (0.0039798) |
| Facebook connections | 0.000155\*\*\* (0.0000387) |
| Usa | 0.228117\*  (0.1126059) |
| Europe | 0.281061\*  (0.1247737) |
| Asia | 0.41  (0.3055882) |
| Africa | 0.74  (0.4393918) |
| Arts & Craft | 0.497420\*\*\*  (0.1316515) |
| Comics & Journals | -0.295620\*  (0.1185179) |
| Technical games | -0.817592\*\*\*  (0.1133283) |
| Theater Dance & Music | 0.546481\*\*\*  (0.0895776) |
| Fashion & Design | -0.972547\*\*\*  (0.1296473) |
| Photo & film | 0.318924\*\*\*  (0.0907904) |
| \_Cons | -0.839001\*\*\*  (0.1499985) |

|  |
| --- |
| \* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01; (Standard errors in parentheses)  Number of obs 9652  LR chi2(17) 4820.65  Prob > chi2 0.0000  Log likelihood -3142.1296  Pseudo R2 0.4341 |

# 4. Discussion of results

The model estimated above performs particularly well in terms of its overall predicting ability. Based on the assumption that whenever the estimated probability of success is larger than 0.5, then a success is predicted, it is possible to derive relevant findings about the model’s ability to predict the project’s successes. These are reported in [Table 3.1](#table31) and [Table 3.2](#table32) below:

**Table 3.1**

Predictive success

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Success or Failure |  | Observed outcomes | |  |
|  |  | **Observed Success** | **Observed Failures** | **Total** |
| Predicted  Outcomes | Predicted Success | 1557 | 292 | 1849 |
| Predicted Failure | 973 | 6830 | 7803 |
|  | Total | 2530 | 7122 | 9652 |
| Total number of correct  Predictions | 1557 + 6830 |  | Percentage of Corrected Predictions  (1557+6830)/9652 | 87% |

Table 3.1 Predictive Success

The first result shows the predicting accuracy of the model. In particular, [Table 3.1](#table31) shows that the *overall percentage of correctly predicted outcomes of the campaign*, given by the sum of *correctly predicted successes* and the correctly *predicted failures,* equals 87%.

The model’s predicting ability can be further decomposed into different prediction categories. These additional results are detailed in [Table 3.2](#table32), below. These show that the model is better at predicting failures correctly, a property defined as *specificity*, than at predicting success correctly, a property defined as *sensitivity.* In fact, the probability of predicting failure, conditional on failure being the outcome, P (PF/ F) equals 0.96, while the probability of predicting success, conditional on success being the outcome P(PS/ S), equals 0.62.

The model’s estimates, in [Table 3.2](#table2), also show a high *Positive Predictive Value*, given by the probability of observing a success when a success would have been predicted, P(S/PS) = 0.84, however this is still lower than its *Negative Predictive Value,* the probability of observing a failure when a failure would have been predicted, P(F/PF) = 0.88. Particularly low is the *Probability of predicting a success when a failure happened*, P(PS/F) = 0.04 indicating the very low chances of making this type of over-optimistic prediction mistake. Much higher is, however, the probability of making the opposite over-pessimistic mistake, the *Probability of predicting a failure when a success happened,* as P(PF/S) = 0.38.

Finally, by looking at the model’s predictive power from an *ex-post* perspective, one can see that the *Probability of observing failure after predicting a success*, is quite low at P(F/PS) = 0.16, but even lower is the ex-post over-pessimistic prediction based on the *Probability of observing success after predicting a failure* P(S/PF) = 0.12.

Table 3.2

**Predictive Analysis**

|  |  |  |
| --- | --- | --- |
| Sensitivity | P(PS/ S) | 0.62 |
| Specificity | P(PF/ F) | 0.96 |
| Positive Predictive Value | P(S/PS) | 0.84 |
| Negative Predictive Value | P(F/PF) | 0.88 |
| Probability of predicting a success when a failure happened | P(PS/F) | 0.04 |
| Probability of predicting a failure when a success happened | P(PF/S) | 0.38 |
| Probability of observing failure after predicting a success | P(F/PS) | 0.16 |
| Probability of observing success after predicting a failure | P(S/PF) | 0.12 |
| Overall probability of predicting correctly the campaign’s outcome | P(PS/S)+P(PF/F) | 0.87 |

Next, the specific effects on the probability of success of innovation projects due to each of the key predictors are discussed in relation to the paper’s hypotheses developed in section 2.

## 4.1 Previously created campaigns: reputation and the role of experience

The first hypothesis addressed the role of experience in crowdfunding, stating *H1: Signalling about a project’s creator experience has a positive impact on the probability of the project’s success*. This hypothesis’s development was based on the idea that experience could be used as a signalling strategy aimed at increasing a creator’s reputation, hence reducing the negative impact of *moral hazard*, due to the presence of ex-ante asymmetric information. The estimates of the model reported in [Table 2](#table2) show that the predictor expressing the number of *previously created campaigns* has a positive and significant impact on the likelihood of the campaign succeeding. Figure 6 below shows the evolution of the probability of a project’s success as a function of the number of previous campaigns already run by the creator of the project, for three different funding goals, at $1000, $5,000 and $10,000.



Figure 6 Probability of success and experience/reputation

This result suggests that experience matters, the more experience a project’s proposer is able to display on the project website, reflected in the number of previously created campaigns on Kickstarter, the more successful it will be at raising funds. This evidence contrasts with the findings of [Colombo et al, (2015)](#Colombo) in which the number of previously created campaigns, as indicators for social capital was not significant in predicting the success of the campaign[[5]](#footnote-5).

Finally, [Table’s 2](#table2) results, evidentiating the positive impact of the number of previously created campaigns, should also be seen as a confirmation for the role of reputation in crowdfunding. Reputation is increasingly important in virtual exchanges as online interaction, on its own, does not entirely replicate many of the tacit aspects otherwise characterizing face to face relations. Reputation is required to establish trust relations, particularly in the finance of innovation environment, as this is characterized by high information asymmetries.

## 4.2 The role of ambition

The second hypothesis developed outlined in section 2 focused on ambition, *H2: A campaign’s project ambition has a positive and significant effect on its probability of success.* From[Table 2](#table2), one can see that the predictor for ambition, provided by a project’s *funding goal* has a negative and significant effect on the probability of success of the campaign, Hence, the evidence would lead to a rejection of H2. Interestingly, while ambition is often seen as a key driver of innovation and entrepreneurship, these results, showing that it has instead a negative impact on the probability of success of innovation projects, provide supporting evidence to [Bernardo and Welch, (2001)](#Belleflameetal) argument that overconfidence may lead to an increased likelihood of failure.

## 4.3 The role of impatience

Concerning the third hypothesis on the role of creators’ impatience, *H3: A campaign’s project duration has a positive and significant effect on its probability of success,* thedata allowedto record a proxy recording the declared duration of the campaign[[6]](#footnote-6). The estimates in [Table 2](#table2), show that the effect of the predictor *project’s duration* on the probability of success is negative and significant hence, the longer the duration of the campaign, the more patient the creator, the less likely the project is to succeed. This negative effect of a project’s duration, reveals the positive aspect of being impatient, leading to the rejection of hypothesis H3. Keeping everything else equal, this can be interpreted as impatience being a signal to early backers to provide early initial funding to kick-start a process of self-fulfilling positive expectations.

## 4.4 Previously backed campaigns: the relevance of reciprocity

In section 2, the fourth hypothesis of the paper was introduced: *H4: Signalling reciprocity, by backing other projects, has a positive impact on the probability of a project success*. H4 was based on the idea that the number of projects a creator has backed can be seen as a proxy for *reciprocity*, as this metrics openly displays direct financial support provided by the project’s creator to other projects of the Kickstarter community. One can see, from [Table 2](#table2), that the predictor for reciprocity has a positive and significant impact on the probability of success of a project. Figure 7 below shows the evolution of the probability of success as a function of the number of other projects backed for three different funding goals.



Figure 7 Probability of success and reciprocity

This result provides further support for the idea that an online platform such as Kickstarter may be pivotal for *strategic signalling*, using reciprocity, to overcome the possible innovation finance market failures due to the possibility of *adverse selection* emerging from *ex-ante* asymmetric information.

## 4.5 External Social Capital

The fifth hypothesis introduced in section 2, addressed the problem of the role played by external social capital in crowdfunding, stating that: *H5: A project’s external social capital has a positive impact on the probability of its success.*

The model introduced in this paper captures the effects of external social capital through the number of Facebook connections, as displayed on the Kickstarter’ project page. The results reported in [Table 2](#table2) show that this predictor has a significant but not particularly strong effect on the probability of success. Figure 8 below shows the evolution of the probability of success as a function of the number of Facebook connections on the project’s page, for three different funding goals.



Figure 8 Probability of success and external social capital

Based on larger and more recent database of projects than previously done in earlier contributions, this finding confirms the significance of the impact on a project success of signalling through the number of the Facebook’s friends of the project’s creators. This result also provides supporting empirical evidence to the work of [Kromidha and Robson, (2016)](#Kromida) arguing that the size of the network of online friends of a project’s creator is key for its success while contrasting [Colombo et al (2015)](#Colombo) results who did not find a significant relations between external social capital and the probability of a project’s success.

## 4.6 Early funding as a predictor of success

The longitudinal nature of the collected data set allows one to test the paper’s sixth hypothesis, introduced in section 2, *H6: Early funding and early backing are critical factors in increasing the probability of a campaign’s success.*The variable *early funds* measures the cumulative amount of the funds raised during the first sixth of the duration of the campaign. The estimation results, in [Table 2](#table2), show that *early funds*, as a predictor, positively affects the probability of success of the campaign.

The variable *early backers* displays the number of backers “*recruited”* during the first sixth of the duration of the project’s campaign. The model estimates, in [Table 2](#table2), clearly show that this predictor also has a positive and significant impact on the probability of a project’s success, confirming the relevance of *early popularity* for a project.

Figure 9 below shows the cumulative distribution of the probability of success as a function of the number of early project’s backers for three different funding goals.



Figure 9 Probability of success and early backers

This evidence supports *H6: Early funding and early backing are critical factors in increasing the probability of a campaign’s success* and the overall interpretation of the funding process as a highly path-dependent one, whereby initial random backers carry nonstrategic signalling externalities that might ultimately determine whether or not a project will emerge as a successfully funded one after traversing the *Valley of death*.

## 4.6 Covariates

To conclude the discussion of the model’s results, this section reports evidence captured, from additional geographic and sectorial covariates, whose impact on the probability of a crowdfunding project success were not discussed as specific research hypotheses in section 2.

### 4.6.1 Geographical location

In the model parameters’ estimates, reported in [Table 2](#table2), one observes that projects housed in Europe or in America benefit from a positive and significant geo-locational effect on the probability of their success. However, an interesting finding also shows that even though Kickstarter was originally started in North America, other things being equal, a project located in Europe had a higher probability of success than one located in North America. This may suggest that there may be an oversaturation of crowdfunding projects on Kickstarter in North America[[7]](#footnote-7).

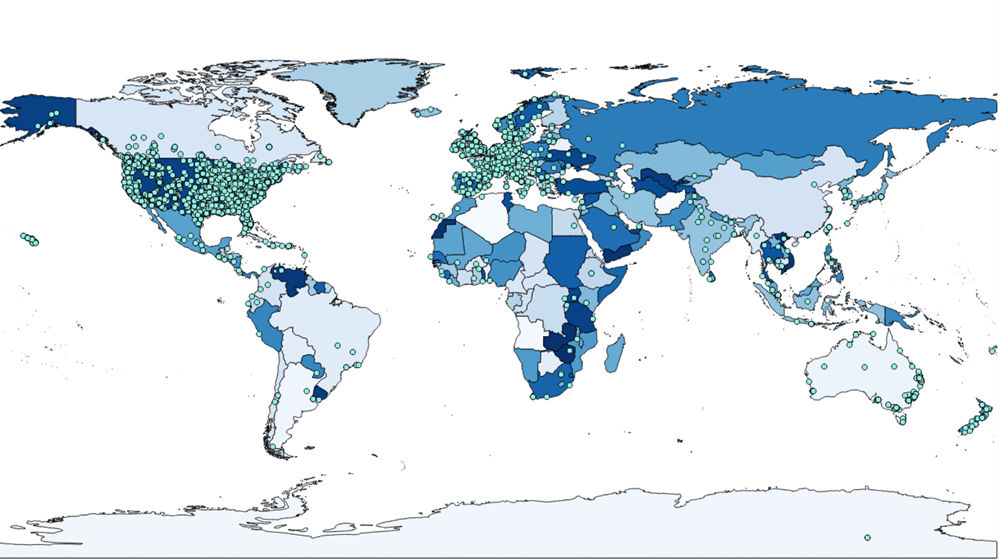


Figure 10 Geographic Location of the projects

The estimates for the geo-location parameters of Asia and Africa were not statistically significant in affecting the probability of a project’s success, suggesting the need to collect more data to consider other countries outside of North America and Europe. Even within North America and Europe, this result by itself is not that useful, as [Mollick (2014)](#Mollick), showed that there is variation in success rates across the United States and thus suggests that to truly capture geographical variance, regional differences across countries should also be considered. While [Kromidha and Robson (2016)](#Kromida) moved in this direction, by introducing a richer geographical representation, their results do not find significant geographical variation effects. Another point to consider is that we only captured the geographical location of the project, and we did not take into account the location of the backers. However, [Agrawal et al, (2015)](#Aker) showed that geographical distance between backers and creators did not greatly impact on the investment patterns of the funders, after conditioning for the creators’ offline social network.

Although significant, it is difficult to draw any clear conclusion from our evidence on the role of geographic location in shaping the probability of success or failure for a crowdfunding project, especially considering the low number of results available from Asia and Africa[[8]](#footnote-8).

### 4.6.2 Categorisation of Crowdfunding projects

Finally, the Kickstarter platform allows projects’ creators to select the specific, product or service, category where the proposed innovation belongs to. As such, the paper considered as additional covariates the specific categories chosen by the creator as displayed in [Table 5](#table5) below and estimated their impact on the probability of success or failure of the project.

Table 5 Combined Categories

|  |
| --- |
| Art and crafts |
| Comics, publications and journalism |
| Technology and games |
| Theatre, dance and music |
| Food |
| Fashion and Design |
| Photo and Film |

The model’s estimates in [Table 2](#table2) present evidence of great differences in the impact of the category dummies with some of them positively affecting the probability of a project’s success. This additional evidence further supports the results of [Kromidha and Robson (2016)](#Kromida) which categorised the projects by SIC code and found that some of the sectors were significant.

# 5 Conclusions

This paper provides extensive evidence on a set of hypotheses developed to identify key predictors for the success and failure of crowdfunding projects through the virtual platform Kickstarter. The hypotheses were separated into two main categories, hypotheses 1 to 3 focus on signalling by the creator of the crowdfunding campaign, while hypotheses 4 to 6 captured the impact of signalling by the network of people related to a crowdfunding project. By accurately predicting over 87 percent of projects’ successes or failures, the model introduced in this paper, not only provides empirical evidence essential in understanding the key role of variables such as external social capital, reputation, reciprocity, impatience and ambition in determining the success or failure of new creative ventures, but also provides a useful tool in the hands of project managers and funders in shaping new strategies for the launch of their campaigns. These insights are based on some of the most up to date evidence, collected by the authors, in a particular moment in history, winter 2016, whereby the diffusion of ICT-enabled platforms sustained the exponential growth of crowdfunding. Furthermore, with reference to earlier contributions on crowdfunding, discussed in the literature review, this paper provides additional and more robust supporting evidence to the concept, also captured in H6 that the time-profile of the support for an innovation project is of key relevance in determining its success or failure. These processes are in fact highly path-dependent, as the probability of success of a project is affected from its early stages when the possible arrival of a sudden wave of backers and/or funds might make the difference between final success or failure.

The paper’s hypotheses were mainly developed within a conceptual framework focussing on the role played by strategic, and non-strategic, signalling, in reducing the negative impact of pervasive asymmetric information, otherwise plaguing the traditional financial channels for early stage projects. In more detail, this paper explored how ICT-enabled crowdfunding platforms may provide the infrastructure and the soft-governance required for signalling the level of a project’s external social capital, the cumulated experience of the creators and their investment in reciprocity, all informative signals necessary to counterbalance the negative effects of adverse selection and moral hazard, that can, otherwise, prevent the mutually beneficial funding exchanges through crowdfunding platforms. Finally, this paper also identifies how ambition can endanger an otherwise successful campaign, while, on the contrary, the impatience of the creator can mitigate the negative impact of ambition to increase the chances of success.

***5.1 Limitations and Recommendations***

One of the limitations of this study is that it only shows evidence from the Kickstarter crowdfunding platform and that it does not show the successful delivery of rewards, after the project. Past studies have shown that there has been a high rate of delivery in Kickstarter, with projects delivering rewards at a rate of over 97.2% [(Mollick 2014, pg 11)](#Mollick). This suggests a possible extension of the work done in this paper into considering post-success problems and the ability of the final delivery of rewards to the community of backers.

As mentioned in the literature review, there are multiple different types of crowdfunding and this paper only captures *reward based* crowdfunding on a single platform. Thus, to expand upon the paper’s findings, one would also need to look at the other types of crowdfunding, to consider the potential differences of predicting successful fundraising between them, further increasing the applications of this model. The method of data capture, using Import.io to web crawl websites is transferable to other crowdfunding sites, giving the possibility of expanding the present set of results and to consider the differences in crowdfunding platforms.

This paper focused on capturing data over a four-month period of time. As such, it does not capture any possible seasonal variation within the dataset. With a longer dataset, on which the authors are currently working, it would be possible to also capture seasonal effects and to consider whether crowdfunding is more or less effective in different parts of the year.

Finally, this paper is relevant not only with regards to the crowdfunding literature but also more generally to the methods used to forecast the diffusion of innovations. This contribution to technological forecasting lies in the paper’s methodology of collecting very early stage information, pre-diffusion, that might be of precious predictive value for all projects not only the successful ones, so as to avoid the selection bias based on the sole observation of successful projects discussed in [Derbyshire and Giovannetti (2017)](#derbhyshire). In this study, failure is no more a counterfactual of success, but a crucial informative element in predicting the early success or failure of innovations, as with crowdfunding the failed projects are visible, they are no more the sunken base of an unobserved iceberg.

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# References

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

Aghion, P., Akcigit, U. and Howitt, P., 2013. *What do we learn from Schumpeterian growth theory?* (No. w18824). National Bureau of Economic Research.

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

Akerlof, G.A., 1970. The market for" lemons": Quality uncertainty and the market mechanism. *The quarterly journal of economics*, pp.488-500.

Arthur, W.B., 1989. Competing technologies, increasing returns, and lock-in by historical events. *The economic journal*, *99*(394), pp.116-131.

Banerjee, A.V., 1992. A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), pp.797-817.

Belleflamme, P., Lambert, T. and Schwienbacher, A., 2013. Individual crowdfunding practices. *Venture Capital*, *15*(4), pp.313-333.

Belleflamme, P., Lambert, T. and Schwienbacher, A., 2014. Crowdfunding: Tapping the right crowd. *Journal of business venturing*, *29*(5), pp.585-609.

Bernardo, A.E. and Welch, I., 2001. On the evolution of overconfidence and entrepreneurs. *Journal of Economics & Management Strategy*, *10*(3), pp.301-330.

Bikhchandani, S. and Sharma, S., 2000. Herd behavior in financial markets. *IMF Staff papers*, pp.279-310.

Branscomb, L.M. and Auerswald, P.E., 2003. *Taking Technical Risks: How Innovators, Managers, and Investors Manage Risk in High-Tech Innovations*. MIT Press.

Cantamessa, M, 2016. “Reconciling forecasting and lean development – open issues”, presented at the 18th IIF Workshop Forecasting New Products and Services Research and Applications, Politecnico di Milano,12 - 13 May 2016 Milan, Italy

Certo, S.T., 2003. Influencing initial public offering investors with prestige: Signaling with board structures. *Academy of management review*, *28*(3), pp.432-446.

Chen, Y.H. and Barnes, S., 2007. Initial trust and online buyer behaviour. *Industrial management & data systems*, *107*(1), pp.21-36.

Cho, I.K. and Kreps, D.M., 1987. Signaling games and stable equilibria. *The Quarterly Journal of Economics*, *102*(2), pp.179-221.

Coleman, J.S., 1988. Social capital in the creation of human capital. *American journal of sociology*, *94*, pp.S95-S120.

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

Connelly, B.L., Certo, S.T., Ireland, R.D. and Reutzel, C.R., 2011. Signaling theory: A review and assessment. *Journal of management*, *37*(1), pp.39-67.

Cumming, D.J., Leboeuf, G. and Schwienbacher, A., 2014, December. Crowdfunding models: Keep-it-all vs. all-or-nothing. In *Paris December 2014 finance meeting EUROFIDAI-AFFI paper* (Vol. 10).

Dai, N., Ivanov, V. and Cole, R.A., 2017. Entrepreneurial optimism, credit availability, and cost of financing: Evidence from us small businesses. Journal of Corporate Finance, 44, pp.289-307.

David, P.A., 1985. Clio and the Economics of QWERTY. *The American economic review*, *75*(2), pp.332-337.

Derbyshire, J. & Giovannetti, E., 2017. Understanding the failure to understand New Product Development failures: Mitigating the uncertainty associated with innovating new products by combining scenario planning and forecasting, Technological Forecasting and Social Change, Volume 125, pp. 334-344.

Desai, S., Acs, Z. and Weitzel, U., 2010. *A model of destructive entrepreneurship* (No. 2010, 34). Working paper//World Institute for Development Economics Research.

Ellison, N.B., Steinfield, C. and Lampe, C., 2007. The benefits of Facebook “friends:” Social capital and college students’ use of online social network sites. *Journal of Computer‐Mediated Communication*, *12*(4), pp.1143-1168.

Fafchamps, M. and Minten, B., 2002. Returns to social network capital among traders. Oxford economic papers, 54(2), pp.173-206.

Fisher, I., 1930. The theory of interest. *New York*.

Giovannetti, E, 2017. Digital Divide and Digital Multiplier: A Paradigm Shift through Innovation, in Lehr, W. and Sharafat, A, eds. “ICT-Centric Economic Growth, Innovation and Job creation” International Telecommunication Union, Geneva, ISBN, 978-92-61-24411-8.

Giudici, G., Nava, R., Rossi Lamastra, C. and Verecondo, C., 2012. Crowdfunding: The new frontier for financing entrepreneurship? Available at SSRN 2157429

Gorton, G. and Winton, A., 2003. Financial intermediation. *Handbook of the Economics of Finance*, *1*, pp.431-552.

Griffin, Z.J., 2012. Crowdfunding: fleecing the American masses. *Case W. Res. JL Tech. & Internet*, *4*, p.375.

Hsiao, C.C. and Chiou, J.S., 2012. The effect of social capital on community loyalty in a virtual community: Test of a tripartite-process model. *Decision Support Systems*, *54*(1), pp.750-757.

Jensen, M.C. and Meckling, W.H., 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, *3*(4), pp.305-360.

Keeley. B, 2007. *OECD Insights Human Capital How what you know shapes your life: How what you know shapes your life*. OECD publishing.

*Kickstarter Stats — Kickstarter, 2016*. [online] Kickstarter.com. Available at: <<https://www.kickstarter.com/help/stats?ref=about_subnav>> [Accessed 22 May 2016].

Kickstarter. 2017-a. Hologram Pyramid HD for Smartphones and Tablets Gadget by Isaias J. Perez —Kickstarter. [ONLINE] Available at: <https://www.kickstarter.com/projects/2112361525/hologram-pyramid-hd-for-smartphones-and-tablets-ga>. [Accessed 20 November 2017].

Kickstarter. 2017-b. OneCook: the Robotic Private Chef to Free Your Cooking Time by Team TNL —Kickstarter. [ONLINE] Available at: <https://www.kickstarter.com/projects/tech-no-logic/onecook-the-robotic-private-chef-to-free-your-cook>. [Accessed 20 November 2017].

Kickstarter. 2017-c. WinnAcademy Robotics - Helping Young Minds with STEM by Mark Winn —Kickstarter. [ONLINE] Available at: <https://www.kickstarter.com/projects/2119389921/winnacademy-robotics-helping-young-minds-with-stem>. [Accessed 20 November 2017].

Kreps, D.M. and Wilson, R., 1982. Reputation and imperfect information. *Journal of economic theory*, *27*(2), pp.253-279.

Kromidha, E. and Robson, P., 2016. Social identity and signalling success factors in online crowdfunding. *Entrepreneurship & Regional Development*, *28*(9-10), pp.605-629.

Kuppuswamy, V. and Bayus, B.L., 2015. Crowdfunding creative ideas: The dynamics of project backers in Kickstarter. UNC Kenan-Flagler Research Paper No. 2013-15.

Lehr, W. and Sharafat, A, 2017. “ICT-Centric Economic Growth, Innovation and Job creation” International Telecommunication Union, Geneva, ISBN, 978-92-61-24411-8.

Levie, J. and Autio, E., 2013. Growth and growth intentions. White Paper, (1).

Lin, M., Prabhala, N.R. and Viswanathan, S., 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, *59*(1), pp.17-35.

Lu, C.T., Xie, S., Kong, X. and Yu, P.S., 2014, February. Inferring the impacts of social media on crowdfunding. In *Proceedings of the 7th ACM international conference on Web search and data mining* pp. 573-582. ACM.

Maskin, E. and Fudenberg, D., 1986. The folk theorem in repeated games with discounting or with incomplete information. *Econometrica*, *53*(3).

Markham, S.K., 2002. Moving technologies from lab to market. *Research-Technology Management*, *45*(6), pp.31-42.

Markham, S.K., Ward, S.J., Aiman‐Smith, L. and Kingon, A.I., 2010. The valley of death as context for role theory in product innovation. *Journal of Product Innovation Management*, *27*(3), pp.402-417.

Massolution, C.L., 2015. Crowdfunding industry report.

Meade, N. and Islam, T., 2006. Modelling and forecasting the diffusion of innovation–A 25-year review. *International Journal of forecasting*, *22*(3), pp.519-545.

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

OECD, 2011. Financing High-Growth Firms: The Role of Angel Investors, OECD Publishing. doi:10.1787/9789264118782-en.

Putnam, R.D., 1995. Bowling alone: America's declining social capital. Journal of democracy, 6(1), pp.65-78.

Riley, J.G., 1979. Informational equilibrium. *Econometrica: Journal of the Econometric Society*, pp.331-359.

Ross, S.A., 1977. The determination of financial structure: the incentive-signalling approach. The bell journal of economics, pp.23-40.

Rothschild, M. and Stiglitz, J., 1976. Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The quarterly journal of economics*, pp.629-649.

Schaer, O., Kourentzes, N & Fildes, R., 2016. Forecasting diffusion with pre-launch online search traffic data, presented at the 18th IIF Workshop Forecasting New Products and Services Research and Applications, Politecnico di Milano,12 - 13 May 2016 Milan, Italy.

Schumpeter, J.A., 1942. *Socialism, capitalism and democracy*. Harper and Brothers.

Sobel J, 2009. Signaling games. In: Meyers RA, Kokol P (eds) Encyclopedia of complexity and systems science. Springer, New York, pp. 8125–8139

Spence, M., 1974. Competitive and optimal responses to signals: An analysis of efficiency and distribution. Journal of Economic theory, 7(3), pp.296-332.

Stiglitz, J.E. and Weiss, A., 1981. Credit rationing in markets with imperfect information. *The American economic review*, *71*(3), pp.393-410.

Thaler, R.H., 1997. Irving Fisher: modern behavioral economist. *The American Economic Review*, *87*(2), pp.439-441.

Townsend, R.M., 1979. Optimal contracts and competitive markets with costly state verification. *Journal of Economic theory*, *21*(2), pp.265-293.

Zheng, H., Li, D., Wu, J. and Xu, Y., 2014. The role of multidimensional social capital in crowdfunding: A comparative study in China and US. Information & Management, 51(4), pp.488-496.

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**Ap****pendix: Table 4.0 Robustness: Estimates for different models including quadratic terms**

|  |  |  |  |
| --- | --- | --- | --- |
| Success or failure | Quadratic Facebook | Quadratic Duration | Quadratic Funding |Goal |
| Previously created campaigns | 0.149637\*\*\*  (0.02) | 0.145441\*\*\*  (0.02) | 0.146212\*\*\*  (0.02) |
| Previous backed campaigns | 0.007859\*\*  (0.00) | 0.008044\*\*  (0.00) | 0.008071\*\*  (0.00) |
| Funding goal | -0.000267\*\*\*  (0.00) | -0.000266\*\*\*  (0.00) | -0.000342\*\*\*  (0.00) |
| Duration | -0.016530\*\*\*  (0.00) | -0.052302\*\*\*  (0.01) | -0.014971\*\*\*  (0.00) |
| Early-funds | 0.001992\*\*\*  (0.00) | 0.001986\*\*\*  (0.00) | 0.002035\*\*\*  (0.00) |
| Early-backers | 0.028193\*\*\*  (0.00) | 0.029753\*\*\*  (0.00) | 0.028299\*\*\*  (0.00) |
| Facebook connections | 0.000428\*\*\*  (0.00) | 0.000155\*\*\*  (0.00) | 0.000163\*\*\*  (0.00) |
| (Facebook connections)^2 | -0.000000\*\*\* |  |  |
|  | (0.00) |  |  |
| USA | 0.224863\* | 0.226123\* | 0.239228\* |
|  | (0.11) | (0.11) | (0.11) |
| Europe | 0.283464\* | 0.279771\* | 0.278592\* |
|  | (0.12) | (0.13) | (0.13) |
| Asia | 0.440912 | 0.401408 | 0.441902 |
|  | (0.30) | (0.31) | (0.31) |
| Africa | 0.741932 | 0.745915 | 0.824147 |
|  | (0.44) | (0.44) | (0.44) |
| Arts & Craft | 0.497165\*\*\* | 0.502663\*\*\* | 0.491470\*\*\* |
|  | (0.13) | (0.13) | (0.13) |
| Comics & Journals | -0.291512\* | -0.296232\* | -0.307130\* |
|  | (0.12) | (0.12) | (0.12) |
| Technical games | -0.801491\*\*\* | -0.826698\*\*\* | -0.827308\*\*\* |
|  | (0.11) | (0.11) | (0.11) |
| Theater Dance & Music | 0.540684\*\*\* | 0.550929\*\*\* | 0.578420\*\*\* |
|  | (0.09) | (0.09) | (0.09) |
| Fashion & Design | -0.965342\*\*\* | -0.977404\*\*\* | -0.954277\*\*\* |
|  | (0.13) | (0.13) | (0.13) |
| Photo & film | 0.311388\*\*\* | 0.319189\*\*\* | 0.336417\*\*\* |
|  | (0.09) | (0.09) | (0.09) |
| (Duration)^ 2 |  | 0.000518\*\*\* |  |
|  |  | (0.00) |  |
| (Funding Goal )^2 |  |  | 0.000000\*\*\* |
|  |  |  | (0.00) |
| \_cons | -0.889532\*\*\* | -0.295410 | -0.746934\*\*\* |
|  | (0.15) | (0.22) | (0.15) |

\* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01; (Standard errors in parentheses)

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2. See Kickstarter specific project webpages for each of the following, holograms ([Kickstarter, 2017-a](#kicka)), home cooking ([Kickstarter, 2017-b](#kickb)) and robotics ([Kickstarter, 2017-c](#kickc)). [↑](#footnote-ref-2)
3. Defined as the final internet based funders who support the campaign throughout its duration, by contributing financial amounts through the electronic platform provided by Kickstarter. [↑](#footnote-ref-3)
4. In some model specifications also the quadratic values of some of the variables were tested. [↑](#footnote-ref-4)
5. [Colombo et al, (2015)](#Colombo) introduced different models, and the number of previously created campaigns was not significant, in their extended probit estimates model (number 3 and 4) that also included as covariates early funding and early backing. [↑](#footnote-ref-5)
6. As observed by an anonymous referee, the declared duration of the campaign may be affected by the fact that the Kickstarter platform suggested a 30 days long duration. This fact will surely influence the duration decisions of each project, however as this is a common public advice available to all projects, it should not introduce significant distortions about the final duration decisions for each single projects. In view of this comment, however impatience could be seen as the deviation, from the advised length of 30 days. [↑](#footnote-ref-6)
7. Within the observed results, 7261 out of 10893 were from America, while only 2458 were from Europe, thus supporting our suggestion that there may be oversaturation in the American market, decreasing the likelihood of a successful Kickstarter campaign. [↑](#footnote-ref-7)
8. We are grateful to an anonymous referee to point us to this evidence. [↑](#footnote-ref-8)