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WHAT DRIVES REWARD-BASED CROWDFUNDING DYNAMICS?

SPEED OF FUNDING IN REWARD-BASED CROWDFUNDING: EVIDENCE FROM KICKSTARTER

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Abstract

Crowdfunding allows entrepreneurs to receive funding for their for-profit, artistic, and cultural ventures from a large number of individuals, namely the "*crowd*". While extant research devoted attention towards funding success, it somehow neglected the relevance about *how fast* such success is achieved. By using data from a sample of 500 projects, this thesis will shed new light on the importance of the founders' actions on the ability to drive the speed of funding and it will offer a description of the driving factors among different projects. The setting of this paper is reward-based crowdfunding, where founders usually give the final product in its earliest version in exchange for the financial pledge, and this work will study the Kickstarter platform, considered one of the best crowdfunding platforms currently available. The results suggest that speed of funding is driven by peculiarity of the project and founders' characteristics, and distinctive team capabilities. In particular, the projected sum of money required and the right campaign length, the team composition with previous experience among founders, and finally the importance of their network size, together with communication and marketing tools makes the project much faster reaching success. Finally, this paper will outline a supplementary analysis and it will investigate how the considered variables differ among project categories.

Introduction

New ventures require different types of resources to achieve success, and the most critical one is capital. In recent years, crowdfunding has grown as a relatively new way of financing new ventures, without the need of searching for traditional sources of investment. In this sense, founders raise capital through the collective effort of the "*crowd*", but in reality friends, family, and potential customers. Startups that rely on crowdfunding to support their projects usually offer investors the final product in the earliest version, equity, debt or simply a sign of gratitude, in exchange for their funding. Amongst all types of crowdfunding, that differs on the relationship between founders and investors, the most common form of crowdfunding is the reward-based one, that has gained traction thanks to the websites *Kickstarter.com* and *Indiegogo.com*.

Compared to traditional settings, crowdfunding requires a radical change in founders' and investors' skills. For founders, the success in crowdfunding is related to the ability to reach a large network instead of spending a huge amount of resources to persuade traditional founders to invest money in a project. For investors, they have now to rely on different skills, knowledge, and availability of resources (Hui et al., 2014) than the ones in traditional settings, where the criteria to choose investors are only resources they provide, and, likewise, support in increasing the network and expertise of the startup.

The existing literature on this topic (Mollick, 2014; Piccarreta & Prandelli, 2015) has been creating theoretical frameworks and also focusing on the empirical contributions on the factors impacting the projects' success. However, they have been devoting attention only to the success of the funding without studying *how fast* the result is achieved. In this work, we attempt to explore what drives the speed of funding among the projects and we shed new light on our understanding of funding dynamics in a crowdfunding setting. In this way, entrepreneurs will be able to extract best practice examples for increasing the probability of successful crowdfunding projects and for achieving greater speed in reaching success.

Specifically, we will give an overview of crowdfunding, explaining who the actors involved in the process are; we will briefly outline the differences of the crowdfunding types, and we will understand why crowdfunding has grown in popularity in recent years. But more importantly, we will try to answer the research question in order to fill in the research gap:

"What influences the speed of funding for successful Kickstarter projects?"

To be able to answer this question, we will analyze the factors that the existing literature has been testing with regard to project success, and we will analyze whether they will also affect speed of funding. To this extent, this paper will be divided into two broad parts. The first one will be focused on which project and team characteristics are relevant for the speed of funding; in particular, it will analyze whether some structural features of the project, such as the amount of money goal and the right length of the campaign have proved to be important (Mollick, 2014). In addition, we will test the team composition in terms of founding the project in a group, and more specifically, the mixed-gender of the group (Hoogendoorn et al., 2013). This is supported even more by the fact that people that already have experience in the field (Dencker et al., 2009) might help achieve success faster. Consistently with the past literature (Hsu, 2007; Gompers et al., 2010; Ahlers et al., 2015), if founders have already previous successful experience, success is even closer.

Conversely, the second part of this work will study the team capabilities of sharing and communicating the features of the project to the audience and indeed to the investors and attracting them to this new idea. In this regard, we will study whether the team should have a relatively big network size and a good degree of network interaction in order to achieve success faster than the other projects (Higgins &

Gulati, 2006). These latter variables will be measured as number of Facebook friends, number of Facebook shares and comments on the project's page (Mollick, 2014). Finally, we analyze the presence of video and other media content on the platform seen as communication tools that make the project more interactive and therefore more attractive for investment funding. In addition to these analyses, we will study whether these variables differ among project categories, in order to have an idea on which characteristics the founders should focus on when launching a specific project.

1. Literature review

1.1. Definition, principles and models of crowdfunding

1.1.1. What is crowdfunding

Crowdfunding is a relatively new phenomenon which is just recently gaining traction in the innovation and entrepreneurship literature. Mollick (2014) defines it as "*an open call, essentially through the Internet, for the provision of financial resources either in form of donation or in exchange for some form of reward and/or voting rights in order to support initiatives for specific purposes*" (p.2).

Indeed, crowdfunding is a particular type of fundraising which mixes microfinance and crowdsourcing. While crowdfunding draws on relatively small individual contributions, its success relies on the large number of individuals triggered by a founders' network in order to achieve a greater amount of exposure (Mollick, 2014). In this sense, founders raise capital through the collective effort of a "*crowd*", more frequently friends, family, and potential customers.

While the definition of crowdfunding provides a general description of the involved actors' objectives, different subcategories of crowdfunding can be defined based on the founders' and investors' goals. In order to develop our theorizing, the distinction among subcategories is going to be defined and analyzed in the following sections.

The diversity is not only between but also within platforms. Earlier studies highlight a high degree of heterogeneity: from fundraising for an artistic project aiming for few thousand dollars, to ambitious research programs, which can collect a few millions (Mollick, 2014).

1.1.2. Actors: founders, investors and platforms

Founders

In this part, we analyze the actors of the crowdfunding campaign and their incentives. Founders are those who are seeking funding for their project or product. While crowdfunding represents an important source for entrepreneurial seed capital (Mollick, 2014; Mollick & Kuppuswamy, 2014), the latter is not the only reason why founders decide to start their campaign. It communicates both to consumers and investors that the product is interesting and it is worthy of a commitment to buy it or to invest in it. As a matter of fact, crowdfunding allows for customer validation and works as a signal of demand for a particular product, which can lead to further funding from other more traditional sources (Mollick, 2014).

The main risks founders face are information disclosure and the risk of being copied. Indeed, if a player replicates the idea and gets to the market faster, the inventor loses the rents of its innovation[1] (Valenciene & Jegeleviciute, 2013). Consequently, also the bargaining power with the potential suppliers is reduced because suppliers are aware of key information, such as the costs structure, released in order to maximize the fundraising effort (Arvidsson & Svensson, 2016). Finally, the investors that fund the project cannot give the strategic support, the industry knowledge, and the relationship with industry experts that a business angel or a venture capital could bring (Valenciene & Jegeleviciute, 2013).

[1] There is a trade-off between low appropriability vs celebrity. If an entrepreneur produces something and someone copies his idea, the first one is already famous and the market might punish the copying player. However, albeit interesting, this goes beyond the scope of research.

Investors

Turning to the actors on the other side of the platform, the investors, they are motivated to invest in a campaign for a number of reasons. First of all, many backers are rallying around their friends' projects. Second, some are supporting people that they may have long admired. Third, many are just inspired by a new idea and they feel that they want to be part of a community, since crowdfunding creates a community participation (Mollick, 2014). Finally, some are inspired by a project's rewards — a copy of what's being made, a limited edition, or a custom experience related to the project, since the backers are always the "*early birds*" and they test the first version of a product. Most investors are repetitive backers, showing the "*community effect"* of crowdfunding; people that fund projects feel satisfied when they see the project in which they invested having success in the market and they are even more motivated to invest again in the future (Mollick, 2014). Investment in crowdfunding projects delivers also non-monetary rewards. Intangible factors, such as direct psychological rewards, social interactions and reciprocity, are able to fill the gap in motivating contributions and overcoming free rider problems (Boudreau, Jeppesen, Reichstein, & Rullani, 2015).

Investors also face the challenge of the extreme uncertainty of early stage projects and information asymmetry. Startups and projects in the seed stage are at a high risk of failure (Valenciene & Jegeleviciute, 2013). Founders can find difficulties during the production processes, and the project might be delayed. Also, there is information asymmetry between founders and investors, since investors cannot access private information about the risk of fraud. The absence of strong informative signals, the uncertainty about whether founders have created a fraudulent page and the consequent risk of wasting time and money remains.

Platform

The platform is a moderating organization that brings the parties together to launch the idea since it provides infrastructure and rules that facilitate the two groups' transactions (Eisenmann, Parker & Van Alstyne, 2006). The two groups are attracted to each other, that is called "*network effect*". In presence of two-sided network effects, the value of the platform to any given user largely depends on the number of users on the network's other side. If the platform matches demand from both sides, value grows; and, since there are network effects, successful platforms enjoy increasing returns to scale (Eisenmann et al., 2006). Clearly, the main goal of these instruments is the success of the projects, since they always receive a fee proportional to the total amount of capital raised[2], but they are also interested to the maximal possible diffusion of the projects on their platform. Media coverage can be particularly convenient to expand the crowdfunding community and consequently increase the number of investors and the revenues; even because users will pay more for access to a bigger network, and margins are improved as user bases grow[3].

However, fueled by the promise of increasing returns, competition in two-sided network industries can be strong. Platform leaders need to find a way for driving out weaker rivals: they can leverage their higher margins to invest more in R&D or lower their prices (Eisenmann et al., 2006). Indeed it is really hard for them to establish and sustain their two-sided networks. The main challenge is to design the platforms' business models, since the key decision here is pricing. As already seen, platform providers for two-sided networks can draw revenue from both sides. However, it makes sense to subsidize certain users, and it is hard to decide which users and for how long (Eisenmann et al., 2006).

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[2] See: http://kickstarter.com

[3] According to Kickstarter (http://kickstarter.com).

1.1.3. Different types of crowdfunding

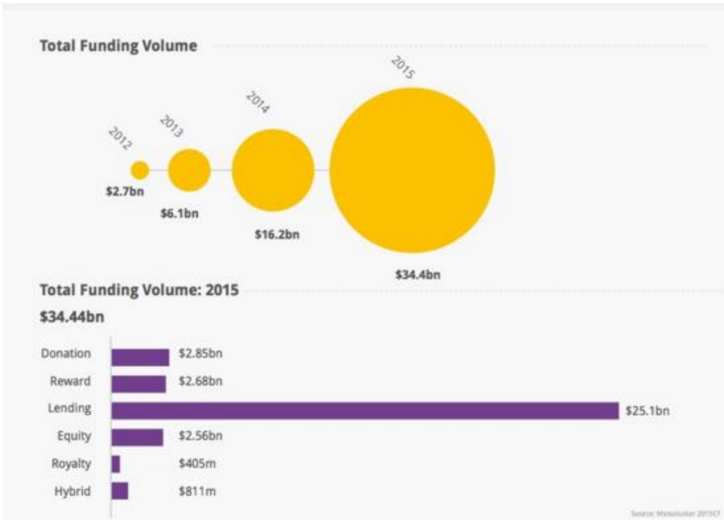
According to Belleflamme, Lambert, and Schwienbacher (2014), the relationship between founders and investors varies by context and the nature of the funding effort. There are four situations in which people fund projects:

1. In the *Patronage model*, funders are considered as philanthropists, in the sense that they do not expect direct return for their donations. It is most commonly used when the project or the campaign is promoted by a non-profit organization or charity, whose main goal is to help an individual, a cause, or a group of people. An example of this is a humanitarian project, like the construction of a hospital or a project that helps children in a third-world country.
2. The *Lending model* refers to the case when a company or a person looks for investors financing a project. In this sense, crowdfunding can be regarded as an alternative to more standard financial institutions. Entrepreneurs propose their projects in search of loans, and investors are considered as lenders supporting a project, as in a sort of virtual bank. However, this system has several advantages: compared to a bank it should yield better interest rates, and the funding process is much faster, thereby time saving.
3. *Reward-based crowdfunding* is the most diffused in the market. Funders receive a reward for backing a project, without interest or part of the earnings of the business. The most common reward is the final product or service of the funded project. Here funders are treated as early customers, having access to the new product, at an earlier date, better price, and with other benefits. Using the product as a reward when campaigning for physical products proves the products' attractiveness while providing the entrepreneurs funding to further develop and market the product. Also, non-tangible rewards are sometimes used, such as having the opportunity of meeting the founders of a project, or being credited in a movie.

4. *Equity crowdfunding* has been studied by different authors such as Mohammadi and Shafizadeh (2015), Dorff (2013), Agrawal, Catalini, and Goldfarb (2016). Funders are regarded as investors or business angels. They invest money in a project in return for ownership or/and repayment with interests. In this sense, they receive equity stakes or similar in return for their funding. However, equity crowdfunding is still the smallest, due to market legislations, and to its complexity. It is more complicated than other forms of crowdfunding and requires the proper checks and balances if it is to provide a viable channel for financial intermediation in the seed and early stage market. Exploring this new channel of funding for young and innovative firms is crucial, given the critical role these start-ups can play (Wilson & Testoni, 2014).

In order to have a big overview of the crowdfunding market, we can state that globally crowdfunding has been rising in the past years. It raised US$6.1 billion in 2013 to US$16.2 billion in 2014 (167 per cent growth) to US$34.4 billion in 2015, according to a research done by Massolution[4].

Figure 1.
Growth by crowdfunding model prediction for 2015 in millions of USD. Source: Symbid (https://e27.co/appeal-reward-based-crowdfunding-kickstarter-indiegogo-20160226/)



[4] See: https://e27.co/appeal-reward-based-crowdfunding-kickstarter-indiegogo-20160226/

As shown in Figure 1, the lending, donation and reward-based models have been driving the growth. Reward-based platforms have volumes of US$2.68 billion. One of the reasons of their success is that they are the easiest forms of crowdfunding, since they are not constrained by laws and legislations, except the VAT and Tax, that need to be followed when selling or rewarding a tangible product. For this and other reasons that we will explain in subsection 1.1.4., this paper will focus on reward-based platforms. The most popular ones within this type of crowdfunding are Kickstarter and Indiegogo, but the main focus will be on the Kickstarter platform, as we will see later on.

1.1.4. Why is reward-based crowdfunding important

Traditionally, when starting a new business or launching a new product, small ventures need to raise capital. However, it is rather difficult to find investors and to be funded at the seed stage. In order to increase the chances of being funded, a comprehensive analytical approach to planning is required in startups (Bhide, 1994). At the base of this approach, entrepreneurs should prepare a business plan illustrating how the entrepreneurial team and idea might be turned into a profitable business. Secondly, they need to do a market research, aiming at evaluating whether the idea has a chance of succeeding in the marketplace. This usually requires collecting information on the industry, on the target market, and on the competition. Finally, they should create prototypes and test them on the market. These are some suggested guidelines in order to attract the funding of investors (Bhide, 1994).

To get the funding, entrepreneurs typically invest their own savings or try to gather money from their closest network - family, friends. They subsequently try to find some angels, high net-worth individuals who typically invest in small, private firms on his or her own account (Wong, Bhatia & Freeman, 2009). Compared to venture capital investors, angel investors do not rely on traditional control mechanisms, such as board control, staging, or contractual provisions to protect against expropriation.

However, they use informal methods of control, such as investing in close geographic proximity or syndicating investments with other angels to mitigate risks (Wong et al., 2009). Only after business angels, venture capitalists come into play. Venture-capital organizations raise money from individuals and institutions available to invest in early-stage businesses with high potential but high risk. Their role is to help entrepreneurs in the search of additional funds, with strategic analysis and management recruiting, also providing the founders with financial and technical expertise, marketing "*know-how*", and business models (Sahlman, 1990).

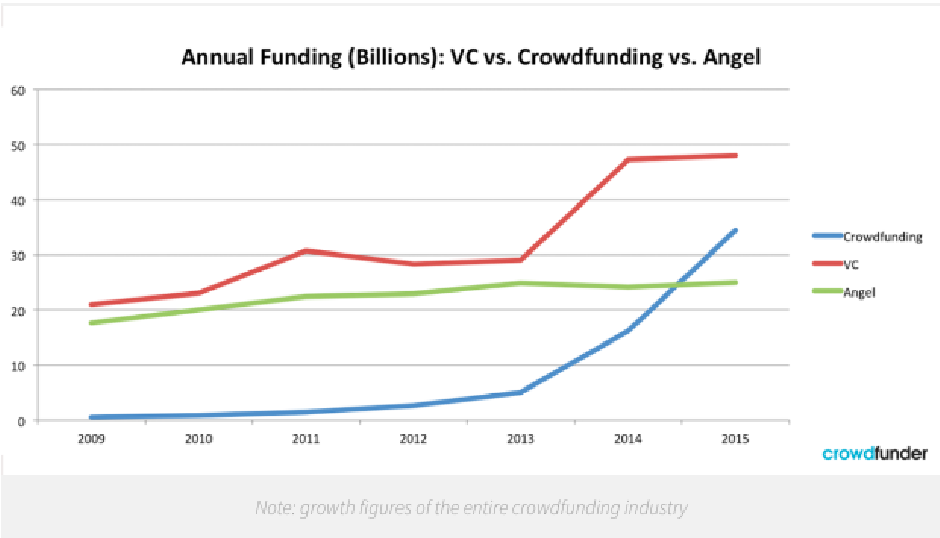
In this sense, traditional investment settings are controlled by few experts with an extended web of networks designed to identify startups. Instead, crowdfunding relies on millions of individuals with different backgrounds, and operates independently of any existing institutional structure in entrepreneurship (Mollick, 2014). Clearly, this new way of financing changes completely the investment settings of the venture in the earliest stages of its life: entrepreneurs now collect small amounts of money from a very large number of people, the "*crowd*" (Bradford, 2012). Thus, crowdfunding allows all types of ventures, but particularly the smallest ones, to be financed, since it is much easier to get the idea in front of millions of individuals online that believe in their project, releasing the fundraising effort from the constraints of geographical and social proximity (Dushnitsky & Kleuter, 2011; Agrawal, Catalini & Goldfarb, 2015).

Compared to traditional settings, crowdfunding requires a radical change in founders' and investors' skills. For founders, the success in crowdfunding is related to the ability to reach a large network instead of spending a great amount of resources to persuade traditional founders to invest money in a project. For investors, they have now to rely on different skills, knowledge, and availability of resources (Hui et al., 2014) than the ones in traditional settings, where the criteria to choose investors are only resources they provide, and support in increasing the network and expertise of the startup.

Besides these aspects, compared to other forms of crowdfunding, reward-based campaigns present other advantages. Such type of crowdfunding allows business owners to motivate their investors without incurring extra expense or selling ownership stakes[5]. Indeed, differently from the other types of crowdfunding, reward-based crowdfunding does not require any interest or equity stakes in the business, but rather it offers different kinds of rewards depending on the amount pledged.

For these reasons crowdfunding is becoming an important alternative in entrepreneurial finance. As we can see in Figure 2, the World Bank[6] estimated that crowdfunding would reach US$90 billion by 2020. If the current trend of doubling year over year continues, it will achieve US$90 billion by 2017. Conversely, VC funding accounts for roughly US$30 billion a year and angel investing for roughly US$20 billion a year.

Figure 2.
Annual funding by type of investing in billions. Source: Symbid (http://blog.symbid.com/2015/trends/crowdfunding-industry-overtakes-venture-capital-and-angel-investing/)



[5] See: https://www.fundable.com/learn/resources/guides/crowdfunding-guide/what-is-crowdfunding

[6] See: http://blog.symbid.com/2015/trends/crowdfunding-industry-overtakes-venture-capital-and-angel-investing/

1.1.5. Reward-based crowdfunding platform: Kickstarter

Today, the most innovative economy in the world, the US, is home to two of the most successful reward-crowdfunding platforms, namely San Francisco-based Indiegogo and New York-based Kickstarter[7]. They are different in two ways[8]:

1. Indiegogo has a technology orientation and it has built a stronger base for new technology products, while Kickstarter funds very different project types, including for example *Arts, Music,* and *Games*;
2. Funding on Kickstarter is "*all-or-nothing*". This means that the project manager sets a goal of reach X amount of money within Y amount of time. In order to get the money, it needs to reach the goal; backers are not charged if a funding goal is not met. Indiegogo is instead in "*keep-it-all*" version, meaning that the project manager keeps what he raised minus the commission from the platform.

We decide to study Kickstarter for three main reasons. First of all, it is the largest and the most established reward-based platform and, according to Forbes, "*it is arguably the most popular crowdfunding platform today*"[9]. In addition, a TechCrunch report shows that for every US$6 Kickstarter raise, Indiegogo would raise US$1 meaning that Kickstarter is much more successful than its nearest rival Indiegogo[10]. Secondly, the main feature that Kickstarter presents is the diversity of categories that it offers since it covers a broad range of projects, including *Arts, Music, Games*, and not only projects related to *Technology*, as we will see in the later sections. Finally, the "*all-or-nothing*" strategy is optimal for our study for two reasons. First, this scheme motivates the founders by making failure more dramatic and raising

[7] See: https://e27.co/appeal-reward-based-crowdfunding-kickstarter-indiegogo-20160226/

[8] See: http://crowdfundingdojo.com/articles/kickstarter-vs-indiegogo-choosing-your-crowdfunding-platform

[9] See: http://www.forbes.com/sites/rakeshsharma/2013/09/04/the-changing-role-of-crowdfunding-platforms-in-the-hardware-ecosystem/#52f74c38302f

[10] See: https://e27.co/appeal-reward-based-crowdfunding-kickstarter-indiegogo-20160226/

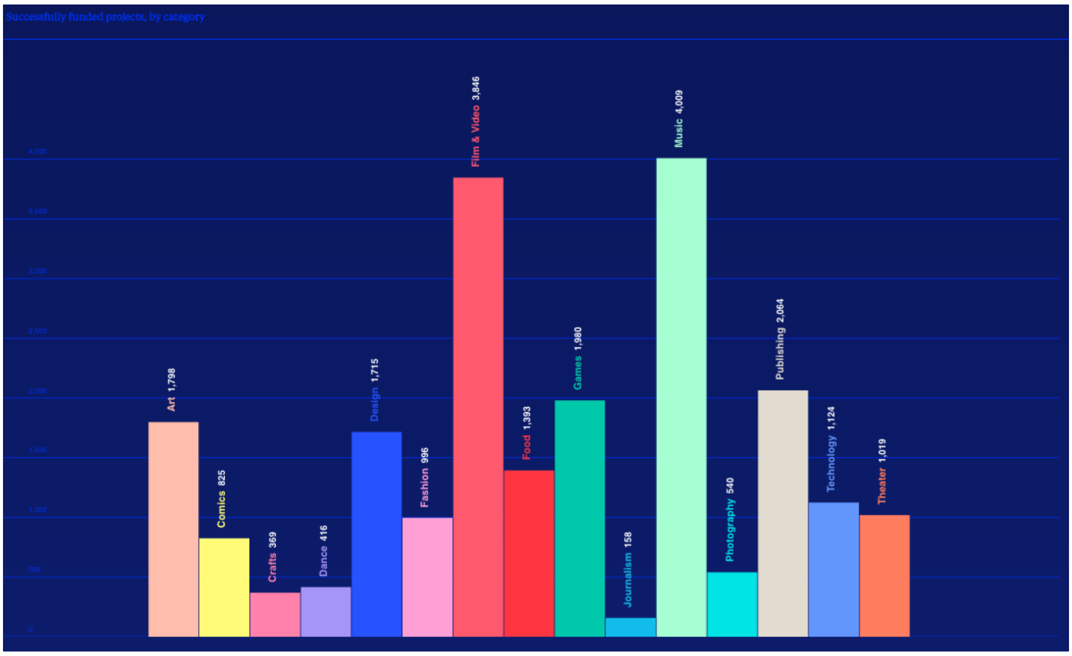
responsibility for the goals to be gained. Second, it encourages backers to pledge more in order to achieve success faster.

Kickstarter was launched on April 28th, 2009 by Perry Chen, Yancey Strickler and Charles Adler, and it is considered a global community built around creative projects. These projects belong to 13 categories, pre-determined by Kickstarter, each having its own section and sub-categories. They include then works in the worlds of *Art, Comics, Dance, Design, Fashion, Film & Video, Food, Games, Music, Photography, Publishing, Technology,* and *Theater*[11]. A project has a clear goal, like making an album, a book, or a work of art and, being that Kickstarter is a reward-based platform, it does not allow projects to fundraise for charity or offer financial incentives. Furthermore, it cannot be used to offer financial returns or equity, or to solicit loans. From the start, Kickstarter raised over US$2 billion from more than 11 million people. In particular, more than 3 million backers are repeated backers. All this money has helped fund over 100,000 project campaigns (Kickstarter, 5th of June 2016).

Focusing only on 2014, 22,252 projects have been funded in one year[12]. Looking at the most funded projects' categories, we could say that *Music* is the first one, followed by *Film&Video,* and *Publishing.* After these, we have *Games, Art, Design, Food, Technology, Theater, Fashion,* and *Comics*. Finally, the least frequent ones are projects within the categories of *Photography, Dance, Crafts,* and *Journalism* (the latter two were added in June 2016).

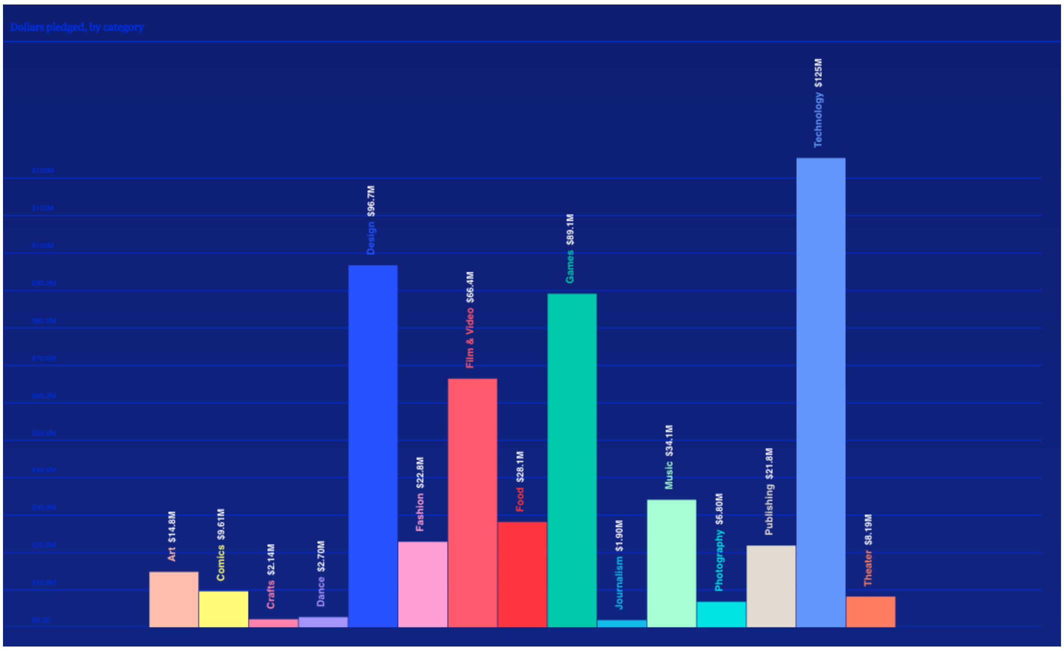
[11] According to Kickstarter itself (https://www.kickstarter.com/).
[12] According to statistics reported by Kickstarter itself (https://www.kickstarter.com/help/stats).

Figure 3.
Successfully funded projects, by category. Source: Kickstarter (https://www.kickstarter.com/help/stats)



Despite this, the average pledged varies among categories. In particular, the most popular categories are *Technology*, that gained US$125M, followed by *Design, Games,* and *Film&Video.*

Figure 4.
Dollars pledged by category. Source: Kickstarter (https://www.kickstarter.com/help/stats)



1.2. Crowdfunding literature

1.2.1. Previous contributions on crowdfunding

In this section, I will briefly review the literature to date and highlight how my study fits into our existing understanding. I will first devote attention to the theoretical frameworks of crowdfunding and then focus on the empirical contributions.

In one of the first contributions, Bruton, Khavul, and Wright (2015) place crowdfunding as one of the recent financial alternatives in seeding entrepreneurship together with microfinance and peer-to-peer lending. Crowdfunding describes how the collective pools together money to support an initiative or project, while microfinance consists in providing financial help to individuals who traditionally lack access to banking and loans; and finally, peer-to-peer lending is defined as for-profit financial transactions occurring directly between individuals or peers without the intermediation of a traditional financial institution[13]. These three methods share the same principle of raising finance from a number of people who pool together and there may be commonalities in the process of speed of funding, extending the contribution not only to crowdfunding but also to peer-to-peer lending.

In this direction, Belleflamme et al. (2014) build a theoretical model of when individuals would choose to invest in crowdfunding. They stress the need to build a community that ultimately enjoys additional private benefits from participation. Indeed, while crowdfunding could be a viable alternative to investor- or creditor-based funding, the mechanisms of investment tend to be closer to donations rather than traditional investment (Boudreau et al., 2015). When joining a crowdfunding project, the more the private benefits the investors receive, the more willing they are to invest right away. Consequently, the project reaches its funding goal faster.

Obviously, the entrepreneurs do not need only to talk about themselves as a team but they also need to decide how to present their idea and approach the investors. Xu et al. (2014) analyze project updates in crowdfunding and they try to understand what brings success. They find out that how project creators communicate with potential funders during a campaign is more predictive of success than the representation of a project page; and also, it seems that projects with frequent updates can almost double the probability of successful funding (Xu et al., 2014). The working paper of Piccarreta and Prandelli (2015) shows temporal variability in funding patterns and that different project's characteristics assume different relevance at various stages of the funding journey. For example, they show that marketing tools (such as videos), the entrepreneur's network size, and prior experience are more effective at the launch of the campaign. Second, they highlight the importance of founder updates to pursue further goals by extending the campaign. This means that a continuous and constant communication between founders and backers is really essential to achieving success. We argue that more prompt communication with the investors may be associated with faster funding.

[13] See: http://blog.lendingclub.com/microfinance-crowdfunding-and-peer-to-peer-lending-explained/

While the existing literature had not focused yet on the speed of funding, several empirical contributions focused on the level of funding as a relevant dependent variable. In the extensive exploratory analysis of Kickstarter, Mollick (2014) and Kuppuswamy and Bayus (2015) show that having a lower money goal increases the probability of being successful. Other studies (De Witt, 2012) confirm that putting some restrictions on the amount of money actually needed maximizes the probability of achieving the chosen funding. This is especially true if the "*all-or-nothing*" rule is applied (the financing is released only if the targeted amount is achieved). Considering again the structural characteristics of the project, it has also been recognized the length of the campaign as a key factor of success. In his blog, *Kickstartup*, Craig Mod[14] theorizes that as the length of the campaign increases it might become difficult for the entrepreneur to foster a high level of interest among the public for the entire period (Piccarreta & Prandelli, 2015).

The existing literature has also studied the importance of the relationship between team characteristics and the level of funding achieved. Mollick (2014) observes that groups perform better than individuals, so it is more likely that a group turns the project into a successful one. This result is due to the network size, since social networks of individuals seeking funds influence the success of entrepreneurial financing efforts. Indeed, a signal of a large social network (high number of Facebook friends) is associated to more successful campaigns but a signal of a small social network is worse than no signal at all (Mollick, 2014). Thus, crowdfunding conforms to the vast entrepreneurship literature arguing that solo founders are a liability (Rocha, Van Praag, Folta & Carneiro, 2016) while teams perform better in crowdfunding as they can rely on larger networks, but this team variable can turn into a liability when it comes to speed of funding as the decision making process during the campaign can be hindered (Sah & Stiglitz, 1988). In this sense, it may be

[14] See: http://craigmod.com/

that, albeit fewer, projects started by solo founders can reach their goals faster as they can adapt their campaign strategy more swiftly.

Other than team versus solo founder, other team characteristics may be relevant. Because it is the most salient team characteristic to observe, the extant literature focused on gender. While Kuppuswamy and Mollick (2015) find out that, as usually expected, men are far more likely to start new ventures than women, there seem not to be difference in the outcome (Marom & Sade, 2013). Greenberg and Mollick (2014) note that female investors tend to support women, especially in technology projects, which is surprising because technology is an industry usually signified by a dominant male gender bias. Experimental results from the entrepreneurship literature inform us that equal gender mix performs better than male-dominated and female-dominated teams because mutual monitoring is more intense (Hoogendoorn, Oosterbeek & Van Praag, 2013). Teams with mixed-gender can outperform single-gender teams in speed of funding as they could leverage the activism of female investors who may invest faster.

Another main point of crowdfunding is the canonical "*jockey vs horse*" question (Kaplan, Sensoy & Strömberg, 2009), that is, whether the project or the entrepreneur characteristics are more salient to investors. For what concerns online angel investment, experimental evidence from Bernstein, Korteweg, and Laws (2015) highlights that the team characteristic is more salient. In crowdfunding, Marom and Sade (2013) find out that technology projects tend to focus more on the business idea, whereas artistic projects focus more on the entrepreneurs. However, in accordance with Bernstein et al. (2015), projects that substantially highlight their entrepreneurs enjoy higher rates of success, controlling for other relevant variables. For what concerns the speed of funding, the result should be the same, since presenting as a team to the investors makes them more attracted to the motivations around the business idea and they should be more willing to invest money.

1.2.2. Gap to cover: Speed of funding

While the existing literature on crowdfunding devoted attention to the success of the funding, it is somehow neglected *how fast* the result is achieved. Studying the key antecedents of project success is the basis for finding a relationship with the speed of funding and it can shed new light on our understanding of funding dynamics in a crowdfunding setting.

We extend our existing knowledge about success of crowdfunding projects starting from the findings of Piccarreta and Prandelli (2015), on the works of Xu et al. (2014) and Mollick (2014) and we contribute to the existing literature with the concept of speed of funding. This analysis adds to an emerging area of research and it will allow entrepreneurs to extract best practice examples for increasing the probability of successful crowdfunding projects and for being much faster in reaching success.

We are going to explain why speed of funding is relevant. Talking about speed in general, according to Kessler (1996) "*innovation speed is important to a firm's creating and sustaining a competitive advantage, especially in rapidly changing business environments*" (p. 1143). In more details, innovation speed is most appropriate in environments characterized by competitive intensity, technological and market dynamism, and low regulatory restrictiveness (Kessler, 1996), which is the case of crowdfunding. In this sense, the existing literature allows us to compare innovation speed to fundraising speed, which is important because it is one of the earliest indicators of success for an entrepreneurial project, and a strong signal to subsequent investors and marketplace.

Thus, speed is a key performance indicator for four reasons (Kessler, 1996). First, faster development is associated with higher rates of learning among team members and their building of core competences related to develop new products. Second, a firm's forecasting is improved when the time it takes to bring a product to market is reduced, because firms are required to make accurate projections about competitors' movements, developments in component technologies, and customers' tastes and expectancies in shorter time periods. Third, speed can increase the quality of a product because it facilitates a greater focus and commitment among workers to project-specific goals. Fourth, if the customers' needs are met, faster product development is associated with relatively higher product quality (Kessler, 1996). To sum up, faster product development is associated with relatively higher project success.

Fast strategic decision-making allows decision makers to keep pace with change and is linked to effective firm performance in high-velocity environments (Einsenhardt, 1989). The findings suggest a configuration of cognitive, political, and emotional processes that is associated with rapid closure on major decisions. This aspect could be reflected in crowdfunding, since it has been seen that being fast during the funding process leads to a greater opportunity for testing, validating and refining the offering. In this sense, the creators could collect feedback and project awareness from the people that invest in the project in exchange for the product itself (Belleflamme et al., 2014).

One of the key success factors for a crowdfunding campaign is achieving and maintaining the right amount of momentum behind the campaign, especially in the early post-launch days. Indeed, once a campaign raises over 20% of the initial funding goal, the project has an 80% chance of successfully reaching its total funding goal. Also, once a campaign hits 30% of its funding goal the success rate climbs to 90% (compared to only 50% after a campaign reaches the 5% mark). The faster the momentum is gained the better: campaigns that reach the 30% mark within the first week have an even higher rate of success[15].

[15] according to statistics reported by Kickstarter itself (http://crowdfunding.cmf-fmc.ca/facts_and_stats/how-likely-is-your-crowdfunding-campaign-to-succeed).

To this extent, the goal of this thesis is to shed more light on the antecedents of speed of funding in a crowdfunding setting with the following research question:

RQ: **"What influences the speed of funding for successful Kickstarter projects?"**

In order to answer this research question, this study will be divided into two broad parts. The first one will be focused on which project and team characteristics are relevant for the speed of funding.

RQ1: "**What is the relation between peculiar project and founders' characteristics and the speed of funding for successful Kickstarter projects?"**

The second part of this thesis will focus on the team capabilities of sharing and communicating the features of the project to the audience and indeed to the investors and making them attracted to this new idea. The question will be formulated like this:

RQ2: **"What is the relation between peculiar team capabilities and the speed of funding for successful Kickstarter projects?"**

In order to answer the first research question, this thesis will test several research propositions. First of all, we talk about the structural characteristics of the project in terms of setting the right amount of money goal and length of the campaign. As already analyzed by the existing literature (Kuppuswamy & Bayus, 2015), the probability of being successful is driven by low money goal and short campaign length, since it is more likely that they reach success and deliver the project on time (Mollick, 2014). To the same extent, we could assume that it is also faster to reach success.

Proposition 1: Projects with low money goal and short campaign length are faster to reach success than projects with opposite characteristics, since the level of funding to reach within the expected time is more reasonable.

Talking about founders' characteristics, we analyze the impact of having a group rather than single projects on the speed of funding. As the existing literature says, larger teams have a higher degree of internal specialization and since the team is composed of different members, each member could have differentiated skills. Furthermore, Mollick (2014) analyzed the impact of networks size on projects' success, and he finds out that group projects are more likely to be successful than projects run by a single person, since personal networks are highly correlated with crowdfunding efforts. Piccarreta and Prandelli (2015) confirm this by saying that larger teams are more likely to have larger social networks, and a larger amount of social capital could be used to achieve financial capital. Due to the fact that speed of funding drives the success of projects, our goal is to analyze whether group projects are faster to reach success than solo projects. We have seen that having a team will most likely bring success, but we need to test if it will bring success more quickly. Furthermore, we are going to analyze whether the gender of the group affects the projects' speed. In the existing literature there are different points of view. Some of them think that men outperform women in starting a new business (Kuppuswamy & Mollick, 2015); others say that female investors tend to support women (Greenberg & Mollick, 2014). The majority of researchers say that an equal gender mix drives success (Hoogendoorn et al., 2013). In this regard the propositions that are going to be tested will be:

Proposition 2a: Group projects are faster to reach success than single projects since they rely on higher degree of specialization and larger network size.

Proposition 2b: Mixed-gender groups reach success faster than mono-gender teams since they bring more differentiated skills.

The third proposition will analyze further whether the group that has already had previous successful experience is faster to be successful again. This concept has always been studied in the existing literature; according to Roure and Maidique (1986), successful entrepreneurs that had prior experience in the same roles that they had in the new venture had fast-rising careers in high-growth units of medium to large companies. And linked to this, they found out that successful companies had a much higher degree of prior joint experience among the members of the founding team than did the unsuccessful companies. By having a management team with previous joint experience (Dencker, Gruber & Shah, 2009), they avoid the waste of resources associated with integrating the different members of the team. In the subsequent years, Colombo and Grilli (2005) stated that prior work experience of founders among technology-based firms exerts a key influence on growth. Similarly, prior work experience in the same industry of the new firm is positively associated with growth while prior work experience in other industries is not. But in order to deep dive into previous experience of the entrepreneurs, the past literature (Hsu, 2007; Gompers, Kovner, Lerner & Scharfstein, 2010; Ahlers, Cumming, Günther & Schweizer, 2015) studied that, if founders have already previous successful experience, success is even closer. This is consistent with the view that if entrepreneurs have market timing skill, and are therefore more likely to succeed, they will be more willing to commit resources to the firm. In this way, success breeds success and strengthens performance persistence.

For what concerns crowdfunding, past success is a signal of quality and reliability that can overcome some of the information asymmetries that are natural in the seed venture financing and in the crowdfunding setting. In the most recent literature, Piccarreta and Prandelli (2015) studied these aspects related to crowdfunding and analyzed how it is likely that one with previous experience can achieve success again. Successful prior experience has been shown to be a determinant of success for entrepreneurial ventures. In some contexts, prior success has a positive and non-diminishing influence in enhancing future performances (Piccarreta & Prandelli, 2015). Hence, entrepreneurs can learn from previous success, but also from failure, because failure makes founders understand what kind of mistakes they made. Indeed, organizational learning literature showed that past failure is a larger learning opportunity than past success (Castellaneta & Zollo, 2014; Madsen & Desai, 2010)[16]. To this regard, we will see whether previous successful experience influences the speed of funding for successful projects by testing this proposition:

Proposition 3: If the team has had previous successful experience it is faster to reach success due to the previous learning.

To answer the second research question, we would like to show whether team capabilities of growing their network size by using communication and marketing tools are relevant for the speed of funding of successful projects. To this extent, the fourth proposition will focus on the size of the network and on its degree of interaction (Higgins & Gulati, 2006). As already studied by Mollick (2014), the role of social networks in funding new ventures has been noted as important. In addition, since many accounts on Kickstarter are linked to Facebook, it is possible to determine how many Facebook connections each founder has. These provide a potential insight into the size of a founders' social network. Furthermore, Piccarreta and Prandelli (2015) study the network size and the impact of network interaction on success, and they find out that friends and close connections could in fact become the first supporters of the project, allowing for a rapid start of the investment process. Indeed, we would like to extend this analysis on the social networks' usage and see whether it allows also a rapid funding of the project. In particular, we are going to analyze the number of Facebook friends, the number of Facebook shares, and the total number of comments on the project's page.

[16] Albeit interesting, we will not analyze past failure as component of the experience for the founders

Proposition 4: If the team has a relevantly large network size and a good degree of network interaction is faster to reach success than projects with small network size and low degree of interaction.

Furthermore, Mollick (2014) and Piccarreta and Prandelli (2015) come to the conclusion that there is a positive relationship between communication and marketing tools and success, but we will further analyze whether videos and other media content, such as images or interactive tools, are also relevant for the speed of funding. The presence of video or other media content might be viral since they could be shared for example on Youtube if we talk about videos, or other social networks for images, and so more people will be involved in the project. In this way, the project seems to be more interactive and investors are more willing to send their money right away to the new project. This is to say that the more communication tools the team uses, the faster will be the achievement of the goals.

Proposition 5: If the team uses video and other media content is faster to reach success than projects that do not use any communication tools since they attract investors more easily and make the project more interactive.

2. Data and methodology

2.1. The dataset

To study the relationship between the speed of funding for successful projects and the explanatory variables – project and founders' characteristics, and team capabilities – we use data on a sample of 500 projects (of which 250 are successful and 250 are unsuccessful), chosen randomly among projects launched on Kickstarter in a specific period time, between October 31st 2013 to November 2nd 2013. We also need to take into account that projects are followed for a maximum of 60 days and before proceeding, we remove the outliers within the projects (55 observations) starting then the analysis with 444 projects.

Our interest is focused on the *time-to-success* that is defined as the time from the start of the project to the achievement of the goal, meaning reaching the 100% of the requested funding. This response variable can take values from zero to 60 days, which is the maximum length of a Kickstarter campaign; however, projects have different campaign lengths, so we decided to normalize them on 60 days. Since we do not have in our dataset values on speed of funding, we calculate *time-to-success* by using the proportion of goal cumulated for each day of the campaign and we consider the day in which the project turned successful as the day in which success is reached. It is important to state that some projects are not successful, meaning that they never reach success in the 60 days of the campaign and the dependent variable for them is missing, in other terms, it is censored. For this reason, a censor variable is created indicating for each project if it is successful or not. In the first case, data are available, while in the latter they are not, so we will then deal with censored data. However, we will explain this further in the next sections.

To individualize the project and founders' characteristics and team capabilities which affect most the speed of funding for successful projects, the following explanatory variables will be taken into account. We consider both information on the projects' campaign and on the entrepreneurs. Relevant "*structural*" aspects include the goal (*Money_Goal*) that is the amount of money to be raised, and the length of the campaign in days (*Campaign_Length*).

Regarding the entrepreneurs' characteristics, we use information on the team composition, that indicated whether the founder is an individual or a team (*Group_Dummy*), and the gender of the team (expressed by the variable *Group_Mixed,* depending on whether the project is founded by mono-gender team or mixed-gender group). Furthermore, we take into account whether the founder has had prior experience with the platform, as measured by the number of projects created and supported on the platform before the considered project (*Projects_Created* and *Projects_Backed* respectively), and how many of the previous projects are successful (*NCreated_Succ)*[17]. Also, we focus on the entrepreneurs' choices as for the presentation of the project on Kickstarter. Specifically, we consider whether or not the project is promoted using a video (dummy variable, *Video*) or other media content, such as other videos, pictures, or music (dummy variable, *Pictures*).

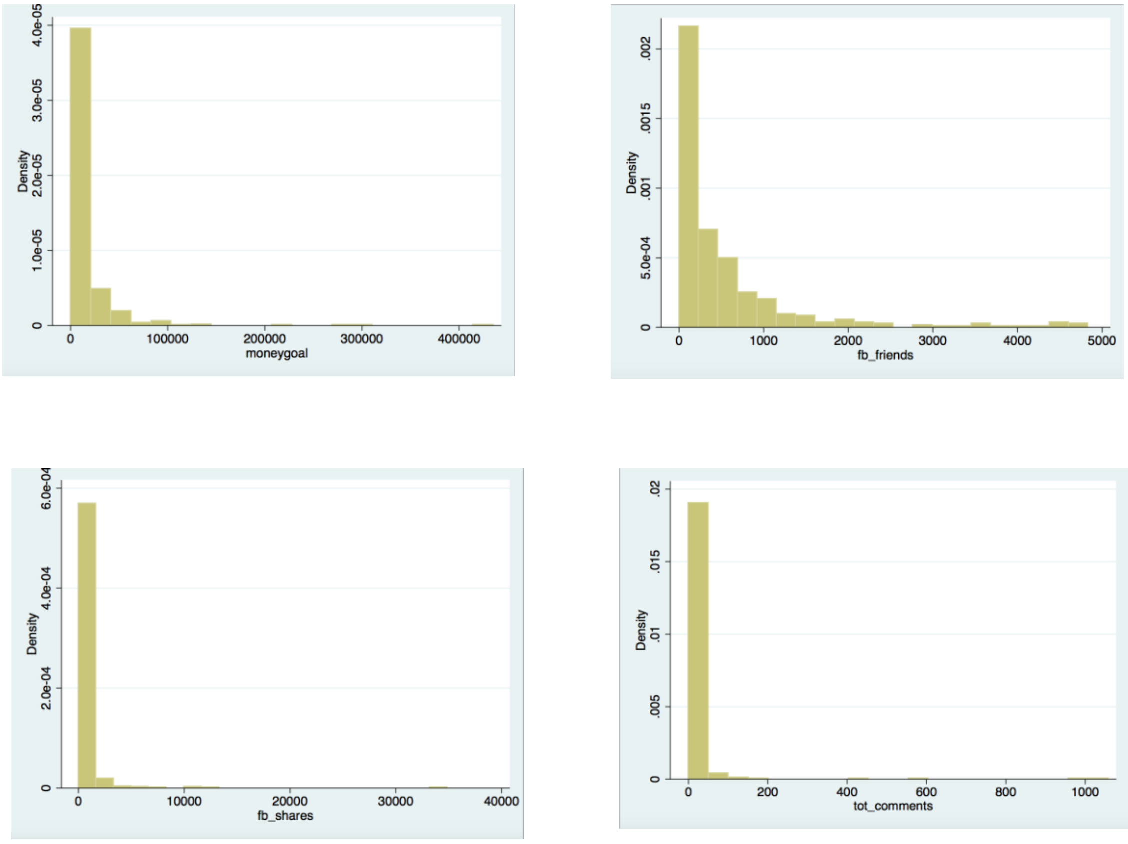
As for the founders' network, we use data on the presence of the founder on the social network Facebook (*Facebook*), and on the size of the network (measured by the number of friends on Facebook, *Facebook_Friends*). Interesting information can also arise by the virality of the projects, which can be measured (or at least approximated) by the number of times it is shared on Facebook (*Facebook_Shares*), by the general comments posted on the project's Kickstarter webpage (*Comments*)[18], as well as by the possible attention received by the projects on websites or newspapers (*Media_Coverage*).

We need to give a few explanations about some variables. First, we transform some variables, namely *Money_Goal, Facebook_Friends, Facebook_Shares*, and *Comments*. We use logarithmic transformations for a simple reason: they are highly right-skewed, meaning that the mass of cases is bunched at lower values, as it is clearly shown in Figure 5. Logarithmic is a convenient means of transforming a highly skewed variable into one that is more approximately normal. Furthermore, we need to underline that the information about the variables related to virality (*Facebook_Friends, Facebook_Shares*, *Comments,* and *Media_Coverage)* refers to the measurements taken at the end of the campaign, so they might be related to the success of the project itself. Finally, since *NCreated_Succ* is linked to the number of projects created and it deals with dimensionality, we prefer to use the percentage of

[17] It is important to state that we do not consider whether the previous projects are in the same category of the current one, but we only analyze the number of previous projects in general.
[18] It is needed to outline that we do not do any analysis on the content of the comments or shares, but we look only at the volume of the reactions.

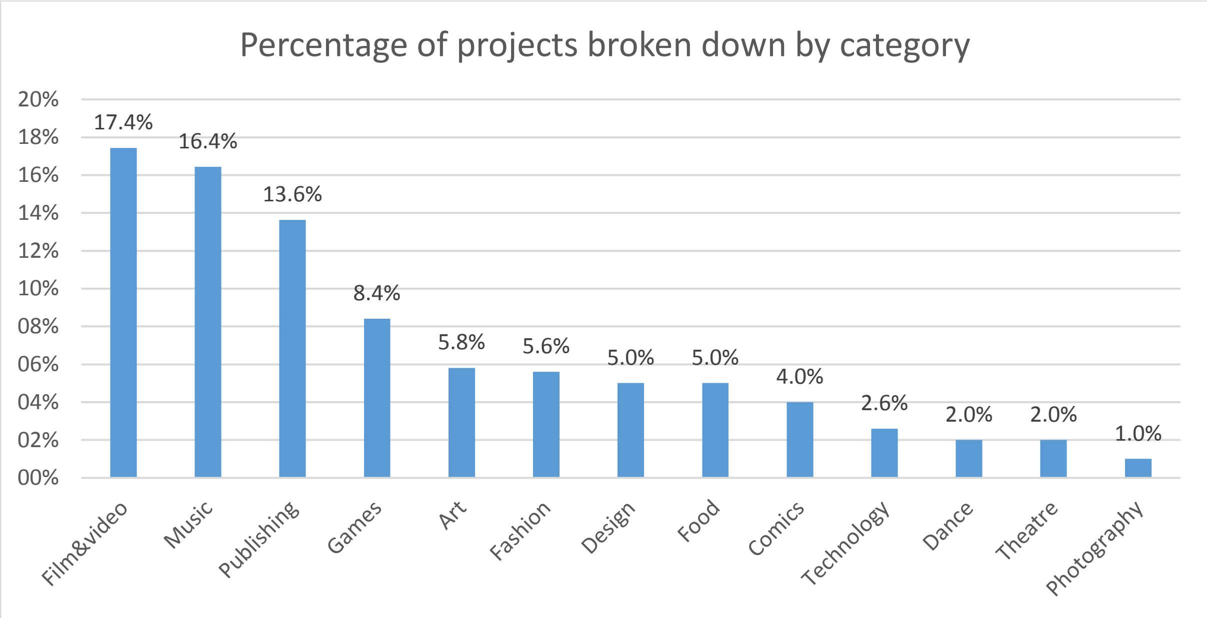
previous successful projects created (*Percsucc_Projects_Created*) in order to avoid repeating the same dimension.

Figure 5.
Transformed variables into logarithmic



Now we describe the mentioned variables on our data. The composition of our selected projects resembles the usage intensity of the platform across the different product categories. In particular, as we can see in Figure 6, the most frequent categories fall into the multimedia categories, such as *Film&Video, Music, Publishing,* and *Games* which include the 17.4% of projects, 16.4%, 13.6% and 8.4% respectively. They are followed by the categories *Art* (5.8%), *Fashion* (5.6%), *Design* (5%), *Food* (5%), *Comics* (4%), and *Technology* (2.6%). Finally, the least frequent ones are *Dance*, *Theatre,* and *Photography* (2%, 2%, and 1% respectively).

Figure 6.
Projects broken down by category



In order to have a general overview of the projects that are included in our dataset, we illustrate the main characteristics of the projects, divided by project category, as we can clearly see in Table 1a. We start considering the length of the campaign. To this regard, we can clearly say that there is no difference among the categories in terms of mean and median, since the general mean and median are 32.99 and 31 days respectively. Looking at the money goal that the projects set at the beginning of the campaign, we notice big differences among categories. *Photography* and *Technology* are the categories with the highest median values ($22,000 and $20,000) and the latter one has a relatively high money goal (the maximum goal is $435,000) and for this reason there is a high level of variability, since the 3rd quartile is the highest among all categories ($45,000). Next, *Fashion, Food,* and *Games* ($10,000) have the second highest median values, followed by *Design* and *Film&Video* ($8,000 and $7,500). In general, they present average dispersion level, but it is interesting to notice that the latter categories have pretty high maximum goals ($275,000 and $215,000). Next, *Theatre, Publishing,* and *Comics* have a median goal around $5,000 and $6,000 and they are characterized by low dispersion and moderate money goal, apart from *Publishing* that has a relatively high money goal ($300,000). Following this, we have *Music, Dance* and *Art* with the lowest median values ($4,800, $4,000, and $2,500 respectively), even if *Art* and *Music* have the maximum money goal really high ($100,000 and $50,000 respectively), whereas *Dance* has a really low money goal ($15,000).

Regarding the success of projects, we can clearly say that the most successful categories – considering a percentage above 50% as successful – are *Theatre* (with 90% of projects that have been funded), *Dance* (70%), *Art* (65%), *Music* (62%), *Design* (56%), *Comics* (55%), and *Film&Video* (51%). To this extent, they are also able to get the highest amount of money, and *Design* is the category that gets the maximum level of money ($7,219 as for median value) with the highest number of backers (84 as per median value). It is followed by *Theatre* and *Comics*, that get $3,886 and $3,422, with 47.5 and 70.5 backers, which is pretty high. Among the mentioned categories, we can say that *Dance, Film&Video, Music* and *Art* receive the lowest amount of money (between $3,000 and $1,200), with an average of 31.6 backers. *Dance, Music,* and *Art* are justified by the fact that they do not ask high money goals, as we have seen before; however, *Art* has the highest proportion of funding (money received/money requested), 3.66, compared to the other categories with lower proportion of funding (1.37 for *Dance*, and 2.70 for *Music*). Finally, *Film&Video* presents a low amount of money received and the lowest percentage of success among the above-mentioned categories, since it requires pretty high money goal, and for this reason the proportion of funding is not relatively high (1.75).

Looking at the categories that get from the 40% to the 30% of success, we can include *Publishing, Food, Games,* and *Technology*. Among them, we can say that *Food* and *Games* get the highest proportion of funding (0.37, and 0.34 as per median values), followed by *Publishing* (0.28), whereas *Technology* is the category that gets the highest money received ($3,146) with relatively high number of backers (32). It can be noticed that the latter category also presents highest variability in money received and proportion of funding. Moreover, *Food* and *Games* also present quite high number of backers (49 for *Food* and 41.5 for *Games*), compared to *Publishing* (19). Considering the least successful categories, *Photography* and *Fashion* fall into this group, with 20% and 14% of success respectively, with relatively low number of backers (8 and 16). It is interesting to notice that these two categories have one of the highest average pledges (money received/number of backers), with $100 for *Photography* and $49.13 for *Fashion*; this means that they have few backers but each backer gives higher amount of money compared to the other categories.

Linked to the previous discussion on the proportion of success, we can start analyzing our dependent variable *time-to-success*, which represents the speed of funding among the different project categories. First of all, we can say that *Theatre, Art, Dance,* and *Music* are the categories with the lowest median values (22, 28, 28.5, and 29 days), the lowest mean values (25.1, 24.76, 25.5, 27.55 days) and they also are the ones with the highest success percentages (more than 60%). This means that they are faster to reach success than the other types of projects' categories; this could be explained by the fact that they require low money goals. To be noticed that *Theatre* has a minimum value of *time-to-success* of 13, meaning that most of the projects fall in the time lapse from 13 to 22 days; and it is interesting to say that *Dance* is the category with the lowest maximum value (32 days). Among the remaining categories, we can say that *Fashion* is the category which has the highest minimum value (16 days) meaning that it never reaches success in the first fifteen days of the campaign, taking into account also the fact that the percentage of achieving success is only 14%.

Table 1a.
Structural characteristics of the projects, broken down by category

Variable	Statistic	Art	Comics	Dance	Design	Fashion	Film& Video	Food	Games	Music	Photogr.	Publishing	Technol.	Theatre
	N cases	29	20	10	25	28	87	25	42	82	5	68	13	10
Days	Mean	32.14	33.65	30.90	33.48	33.29	33.50	32.84	33.52	33.27	32.8	32.84	35.15	31.60
	Median	31	32	31	31	31	31	31	31	31	31	31	31	31
Goal	Mean	10,561	13,032	6,576	30,194	12,285	19,417	15,735	18,419	7,172	17.040	12,039	63,336	7,920
	Median	2,500	6,000	4,000	8,000	10,000	7,500	10,000	10,000	4,800	22,000	5,775	20,000	5,500
	Q1	550	3,000	3,000	3,500	5,000	2,000	6,000	5,000	1,500	15,000	3,000	8,000	2,000
	Q3	8,500	24,500	10,000	25,000	16,500	20,000	20,000	24,000	10,000	22,000	9,554	45,000	15,000
	Min	500	1,000	600	200	1,500	300	1,000	800	200	1,200	500	380	2,000
	Max	100,000	56,000	15,000	275,000	40,000	215,000	70,000	100,000	50,000	25,000	300,000	435,000	20,000
Money received	Mean	10,414	10,062	3,986	10,644	3,158	7,519	9,265	8,702	5,195	3,326	4,609	9,746	7,223
	Median	1,225	3,422	3,002	7,219	880	2,000	2,602	2,209	1,733	880	991	3,146	3,886
	Q1	407	1,118	822	918	56	401	775	342	435	275	178	136	2,331
	Q3	8,706	7,976	4,094	14,532	3,019	6,118	16,528	10,040	5,640	3,510	6,308	11,707	11,801
	Min	0	51	25	30	0	0	51	4	0	100	0	0	410
	Max	116,655	75,350	19,163	39,716	30,342	87,190	48,813	55,422	54,268	11,866	47,691	61,537	20,370
Average pledge	Mean	48.46	38.30	58.20	66.69	51.39	82.50	82.91	49.12	52.52	96.25	56.22	65.20	134.50
	Median	37.14	37.44	52.56	49.17	49.13	66.66	48	33.12	48.10	100	43.69	35	67.31
Nr of Backers	Mean	160.31	244.00	63.40	155.40	52.11	87.84	126.40	251.83	85.42	34	63.98	131.30	72.10
	Median	27	70.5	37.50	84	16	29	49	41.50	33	8	19	32	47.50
Success	%	0.65	0.55	0.70	0.56	0.14	0.51	0.44	0.36	0.62	0.20	0.46	0.31	0.90
Prop. of Funding	Mean	1.12	0.91	0.60	0.93	0.86	0.65	0.77	0.71	0.83	0.70	0.59	0.43	1.02
	Median	1.01	1.04	0.83	1.06	0.26	1.00	0.37	0.34	1.04	0.04	0.28	0.12	1.05
	Q1	0.08	0.09	0.10	0.88	0.06	0.04	0.13	0.04	0.05	0.02	0.02	0.02	1.03
	Q3	1.51	1.44	1.22	1.53	0.37	1.1	1.14	1.32	1.15	0.54	1.08	1.00	1.25
	Min	0.00	0.01	0.002	0.003	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
	Max	3.66	2.51	1.37	2.91	1.21	1.75	3.47	2.68	2.70	2.92	2.36	1.39	1.28
Time to success	Mean	24.76	24.65	25.5	26.96	33.71	30.67	29.2	27.40	27.55	28.4	30.2	32.46	25.1
	Median	28	30.5	28.5	32	32	32	32	32	29	32	32	32	22
	Min	2	6	3	3	16	8	6	2	3	5	2	5	13
	Max	54	36	32	47	60	60	60	59	60	46	59	47	57

Looking at Table 1b, we can also say that projects differ in terms of characteristics of the founder and capabilities of the team of sharing the project and using communication tools. By analyzing the presence of a group team, it is clear that projects falling into *Dance, Theatre, Food, Games, Film&Video, Design,* and *Technology* are proposed by teams frequently since the percentage of group presence is higher than 60%, reaching all projects formed by groups in case of *Dance* and *Theatre* categories. Next, *Fashion, Comics, Music,* and *Art* have a percentage of around 50%, meaning that one out of two projects is a team project. *Publishing* has a really low percentage of group presence (29%), since they are most likely to be solo projects, and finally *Photography* is always a solo project.

If we consider the composition of the team in terms of its gender, we see that *Dance* is always founded by mixed groups, and to a lesser extent *Theatre* (90% of projects are founded by mixed groups). Next, *Games, Film&Video, Food, Design, Technology,* and *Fashion* have a high percentage of being founded by mixed groups (between 74% and 52%). To a lesser extent, *Comics, Music, Art,* and *Publishing* have percentages from 50% to 25%. And finally, *Photography* is always founded by mono-gender teams.

Regarding the virality of projects, we can clearly say that *Food, Comics,* and *Art* are the categories in which the founders have more probability to be registered on Facebook (more than 80%). To this regard, *Theatre, Dance, Art, Music,* and *Comics* have larger networks in terms of number of friends, since they have more than 300 Facebook friends in median and around or more than 500 in terms of means. Conversely, *Technology,* and *Games* are the ones with the smallest networks (with means lower than 200 Facebook friends), even if they have a probability of having Facebook around 60%.

Supporting even more the projects' virality, we can clearly say that almost all projects have a video embedded in their description; however, categories such as *Comics, Design, Photography* and *Technology* always have one. In addition to this, *Comics, Design, and Photography* always have other media, apart from videos, such as pictures or music. If we look at the total number of comments on projects' page, we can say that *Games* is the category with the highest number of interactions (reaching 1,058 comments as a maximum number), with a mean of 90.26 comments, followed by *Comics* (127), and *Food* (98). Conversely, *Dance, Theatre,* and *Photography* have the lowest number of comments, around 3. Finally, looking at the sponsoring of projects on websites or newspapers, we can say that *Games, Design, Technology,* and *Comics* are the categories with highest probability, but still around 20%.

Focusing on the previous experience of entrepreneurs, considered as the number of projects backed and created, we can clearly see that the most experts are the ones in *Music* category, since they created more projects and in particular more successful ones. These are followed by entrepreneurs in *Food* and *Publishing*. To be noticed that these categories are characterized by some serial entrepreneurs (by looking at the maximal numbers of created projects). Looking at the number of projects backed, we can say that entrepreneurs working in categories such as *Games*, *Comics, Film&Video, Publishing* and *Food* backed more projects than other categories. It is impressive to notice that *Games* also overcomes 100 projects backed (120).

Table 1b.
Structure of the proponents (selected variables), broken down by category

Variable	Statistic	Art	Comics	Dance	Design	Fashion	Film& Video	Food	Games	Music	Photogr.	Publishing	Technol.	Theatre
	N cases	29	20	10	25	28	87	25	42	82	5	68	13	10
Group	%	0.48	0.55	1.00	0.68	0.57	0.76	0.88	0.76	0.55	0.00	0.29	0.61	1.00
Group_mixed	%	0.39	0.50	1.00	0.64	0.52	0.72	0.72	0.74	0.47	0.00	0.25	0.54	0.90
Facebook	%	0.83	0.85	0.60	0.80	0.68	0.64	0.92	0.64	0.66	0.80	0.79	0.61	0.80
FB_Friends	Mean	655.31	605.20	536.7	310.56	450.96	599.29	628.28	131.30	713.27	303.20	544.22	169.15	512.00
	Median	363.00	308.00	412.50	219.00	264.50	266.00	273.00	45.50	313.00	205.00	287.00	43.00	468.00
	Max	4,444	3,831	1,457	1,161	1,734	4,551	4,121	966	4,825	856	4,836	981	1,098
FB_Shares	Mean	2015.52	529.35	446.50	742.84	214.54	627.36	390.16	187.52	464.11	124.40	268.31	529.92	278.60
	Median	99	229	294.50	339	83.5	158	232	74	201	77	78	169	208.50
	Min	0	1	91	0	0	0	0	0	0	5	0	0	33
	Max	34,861	2,500	1,114	5,175	1,731	12,935	1,374	1,448	6,131	343	2,396	4,396	712
Video	%	0.90	1.00	0.90	1.00	0.79	0.95	0.96	0.95	0.95	1.00	0.88	1.00	0.90
Pictures	%	0.83	1.00	0.60	1.00	0.86	0.68	0.88	0.90	0.62	1.00	0.54	0.85	0.80
Comments	Mean	6.24	20.25	0.5	13.4	2.71	1.75	7.28	90.26	2.82	1.20	1.72	8.54	0.7
	Max	53	127	3	56	33	43	98	1,058	64	4	18	36	4
Media Coverage	%	0.07	0.20	0.00	0.28	0.07	0.09	0.12	0.29	0.05	0.00	0.07	0.23	0.10
Proj_Backed	Mean	2.86	10.65	1.30	2.96	1.25	2.68	4.72	10.19	1.40	3.40	2.12	1.85	3.2
	Max	13	57	6	13	12	41	37	120	13	7	38	13	11
Proj_Created	Mean	0.17	1.00	0.40	0.28	0.07	0.14	0.80	0.57	1.51	0.20	0.37	0.16	0.00
	Max	2	5	2	2	1	2	19	6	104	1	14	1	0
NCreated_Succ	Mean	0.03	0.65	0.40	0.08	0.04	0.08	0.32	0.19	1.18	0.20	0.26	0.08	0.00
	Max	1	5	2	2	1	2	8	3	88	1	14	1	0

From the summary statistics of the projects, it is pretty clear that projects differ in structural features, founders' characteristics, but also in team capabilities of using communication tools and sharing the projects to make them interactive. However, these statistics are not enough and we want to go further by knowing more about the differences of projects in order to understand better what drives the speed of funding for successful projects. To this extent, in the next sections we will explain the different models that are going to be used to investigate more about speed of funding.

Before proceeding, it is important to say that this thesis analyzes data in a static way, meaning that we do not consider the evolution of variables for each project throughout the campaign; rather, we study the conditions of the variables at the beginning of the campaign or at the end (the latter only for virality variables, as above-mentioned).

2.2. Modelling the *time-to-success*

2.2.1. Possible limits of standard linear regression model (OLS)

We are interested to measure the *time-to-success*, and to relate it to the characteristics of the project and on the founders described in the previous section. However, we need to remember that our data is censored, meaning that there are missing values for the unsuccessful projects, because they do not reach success during the 60 days of the campaign.

In this regard, it is not possible to use linear regression to model *time-to-success* as a function of a set of predictor variables, and for this reason, we need to understand which models can overcome this problem. To be more precise, we need models that take into account two challenges: the first one is that data are discrete, but more importantly, they need to treat the censoring issue. Now we are going to understand these issues further (Woolridge, 2015):

1. The data are discrete: since the maximal length of the campaign is 60 days, the dependent variable takes only values between 1 and 60 (and, importantly *only* if the project is successful). The linear regression is not well-suited for analyzing this dependent variable since it usually deals with continuous variables that can be any real number. Indeed, the normal distribution allows any value on the number scale, but, in our case, counts are bounded at 0, meaning that survival times are typically positive numbers because time can only be positive; and for this reason they have a skewed distribution. Ordinary linear regression may not be the best choice unless these times are first transformed in a way that removes this restriction;

2. Ordinary linear regression cannot effectively handle the censoring of observations, which are censored because the information about their survival time is incomplete. Usually, standard regression and ranking models ignore the data about failed projects since the failed ones do not have the information about the actual success and are considered missing data. In this way, they can only consider the successful projects. Our work instead includes both successful and failed projects.

In order to overcome the first problem, there are several models that are able to study variables with integer values. We can cite for example the logistic, that models indeed ordinal variables and it would be able to deal also with discrete data. However, to solve this non-negative nature of the data, but more importantly the censoring problem, we decide to use censored regression models.

2.2.2. The survival model

In our model, the projects that do not reach success are viewed as the censored instances and successful projects as the uncensored instances. Such censored models seem to have more advantages, but, we need to be clear that they are not seen as alternatives to standard regression models, rather, they are applicable to more specialized and complex modeling scenarios, namely, modeling "*Time-To-Event*" data. As Li, Rakesh and Reddy (2016) say in their paper, the incorporation of failed projects can significantly help to build a robust prediction model and these censored models can perform better than standard prediction models that are available in the literature.

As above-mentioned, our censoring models will contain two main components:

- *Time-to-success*, time taken for a specific event of interest (project success) to occur
- Censoring, partial information of projects where success does not occur

The best model to deal with censoring variables is the survival analysis method. In survival analysis the focus is on examining the time until a specific event or endpoint. The variable that we measure, T, is called the survival time, event time or failure time; in our case, it is *time-to-success*. In some occasions however, we do not observe the event for all individuals or items that we study the survival time for. The real event time will then be unknown and we say that the survival time is censored.

Survival time:

Survival analysis is a part of statistics that focuses on examining data that occur in the time from a given starting point and the time observed for a specific event or endpoint. Since the maximum time period a project can last is 60 days, the creator can choose any survival time T from 0 to 60 days for the project duration, and it is often a discrete random variable. In this crowdfunding problem, for each project, its starting day is considered to be the first day of our study time scale; thus, the maximum value of the actual observed successful or failed day is 60. We need to take into consideration that projects do not start the same day, rather they have different starting time.

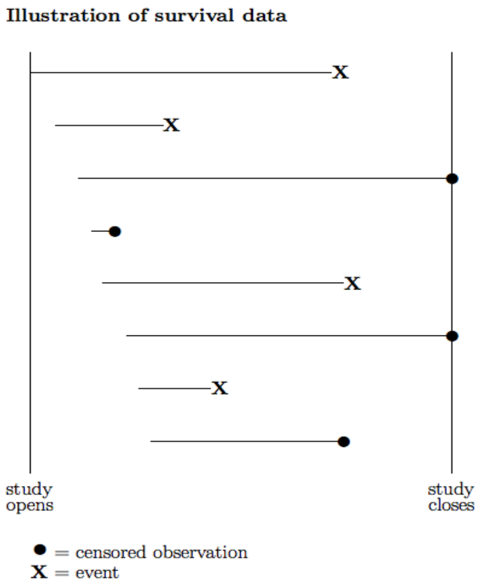
Censoring:

In some situations, we do not observe the event for all individuals that are included in a study, and the exact survival time will then be unknown. For this, we say that the observation is censored. Whether an observation *i* is an event time or a censoring time can be denoted by the event indicator ∂_i. If we observe an event we have $\partial_i = 1$, and if we observe a censoring time we have $\partial_i = 0$.

The most common form of censoring in survival analysis is Right Censoring, and occurs when the event happens after we stop observing the individual. The censored time will therefore be smaller than the actual survival time. In our specific case, the projects that are still "alive" when the study ends, meaning that they have not reached the goal in 60 days will be right censored.

Assumption: Regardless of the type of censoring, we must assume that it is non-informative about the event; that is, the censoring is caused by something other than the impending failure.

Figure 7.
Illustration of survival data. Source: Woolridge, 2015



In Figure 7, we notice three situations:

- Projects do not all enter the study at the same time → staggered entry
- When the study ends, some projects still have not had the event yet → censoring
- Other projects drop out or get lost in the middle of the study, and all we know about them is the last time they were still "*free*" of the event → censoring

For the *ith* project, let define U_i as the predefined project duration and it takes T_i days to reach the project goal amount. T_i is a latent value for failed projects since it does not reach its goal amount during the predefined project duration. Each project can be presented by a triplet (X_i , Y_i ,and ∂_i), where X_i is *1*m* project feature vector, and ∂_i is the project failure indicator, as already said ($\partial_i = 1$ for a successful project, and $\partial_i = 0$ for a failed one).

The observed time Y_i for a project is then defined as follows:
$Y_i = T_i$ if project is successful ($\partial_i = 1$)
$Y_i = U_i$ if project is failed ($\partial_i = 0$)

Our goal is to estimate T_j for a new *jth* project whose feature descriptors are represented by X_y. It should be noted that T_j will be a non-negative continuous value in this case. Following this, the dependent variable in survival analysis is composed of two parts: one is the time-to-event and the other is the event status, which records if the event of interest occurred or not. One can then estimate two functions that are dependent on time, the survival and hazard functions.

- The *survival function* gives, for every time, the probability of surviving (or not experiencing the event) up to that time. It is defined as follows: $S(t) = Pr\ (T\ >= t)$, where it is the probability that the time-to-event is no earlier than a certain specified time *t*. In our case, the project success is the event of interest and *T* is the success date; hence, $S(t)$ is the probability that the project does not succeed after *t* days from the project starting date and it is called the unsuccessful probability. It will be a right-continuous, non-increasing function of *t*, and as clearly depicted in Figure 8, it is with $S(t) = S(0) = 1$, which means that the probability of surviving past time 0 is 1. Instead, $S(t)\ =\ S(\infty)\ =\ 0$, as time goes to infinity, the survival curve goes to 0. The cumulative death distribution function $F(t) = 1 - S(t)$ can be called the cumulative successful probability which tells the probability of reaching the goal within *t* days.

  In order to analyze survival functions, there are different methods:
  - Parametric methods, in which *T* is defined with a particular functional distribution and the hazard function is also fully depicted. They are based on some popular distributions for estimating survival curves such

as Weibull, exponential and, log-normal ($\log(T)$ has a normal distribution)

- Semi parametric methods, in which the distribution of T is not fully defined. These are based on the Cox model.
- Nonparametric methods, in which the distribution of T is not defined. In this case, the tool used for building the survival curves and for measuring the hazard function is the Kaplan-Meier in which the hazard function is not specified.

Usually, when no event times are censored, a non-parametric estimator of $S(T)$ is $1 - Fn(t)$, where $Fn\,(t)$ is the empirical cumulative distribution function. The empirical estimate of the survival function, $S^{\sim}(t),$ is the proportion of individuals with event times greater than t.

$$S^{\sim}(t) = \frac{\#\, individuals\ with\ T \geq t}{total\ sample\ size}$$

However, in our case, some observations are censored, so we can estimate $S(t)$ using the Kaplan-Meier product-limit estimator, which is a very useful tool for estimating survival functions. It involves computing of probabilities of occurrence of event at a certain point of time and multiplying these successive probabilities by any earlier computed probabilities to get the final estimate. The survival function is represented by a decreasing step function with jump at each discrete failure time. It starts at 1 since everybody at time 0 is present, it decreases overtime, and it changes value only when it observes an event. The height of the jumps depends on the number of events and number of projects at risk and censored. The formula of Kaplan-Meier method is:

$$\hat{S}(t_{(j)}) = \prod_{i=1}^{j} \hat{P}\mathrm{r}(T > t_{(i)} \mid T \geq t_{(i)}) = \hat{S}(t_{(j-1)}) \times \hat{P}\mathrm{r}(T > t_{(j)} \mid T \geq t_{(j)})$$

- The *hazard function* gives the potential that the event will occur, per time unit, given that an individual has survived up to the specified time. It is the probability of death at time *t* given survival up to time *t*. The formula is as follows:

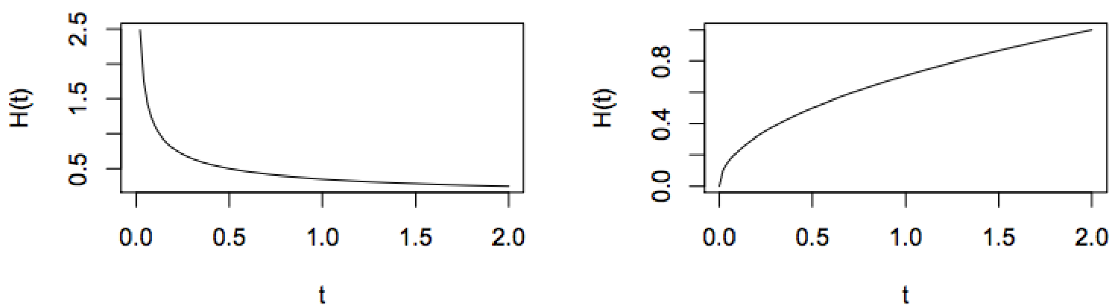
$$h(t) = \frac{\partial F\ (t)}{\partial t} = \frac{\left(F\ (\ t + \partial t) - \ F\ (t)\right)}{\partial t}$$

where $\partial t > 0$ is a short time interval, and it represents in our case the successful probability of reaching the goal at day *t.* In order to estimate this, we use the Nelson-Aalen estimator, which estimates the hazard at each distinct time of "*death*" as the ration of number of deaths to the number exposed. The formula is:

$$\widehat{\Lambda}(t_{(i)}) = \sum_{j=1}^{i} \frac{d_j}{n_j}$$

The cumulative hazard describes the accumulated risk up to time *t*, $H(t)$=$\int_0^t h(u)\,\partial u$, and it is simply the sum of the hazards at all deaths time up to *t*. It is an increasing function starting at zero and increasing as the time increases, as it clearly shown in Figure 8.

Figure 8.
Survival and Cumulative hazard functions. Source: Columbia University (http://www.stat.columbia.edu/~madigan/W2025/notes/survival.pdf)



If we know any one of the functions $S(t), H(t)$, or $h(t)$we can derive the other two functions.

$$h(t) = -\partial \log \frac{(S(t))}{\partial t}$$
$$H(t) = -\log(S(t))$$
$$S(t) = \exp(-H(t))$$

It is possible to then compare curves for two different groups of subjects. For example, in our case we can compare the survival pattern for successful projects and unsuccessful ones. The two survival curves can be compared statistically by testing the null hypothesis i.e. there is no difference regarding survival among two interventions. This null hypothesis is statistically tested by another test known as log-rank test (non-parametric test) and Cox proportion hazard test (semi-parametric model); the latter allows analyzing the effect of several risk factors on survival. The log-rank test is used to test the null hypothesis that there is no difference between the groups in the probability of an event (here success) at any time point. For each such time we calculate the observed number of deaths in each group and the number expected if there are in reality no difference between the groups[19]. The formula is:

$$\text{Log-rank statistic} = \frac{(O_2 - E_2)^2}{Var\ (O_2 - E_2)}$$

The Cox method does not assume any particular "survival model" but it is not truly nonparametric because it does assume that the effects of the predictor variables upon survival are constant over time and are additive in one scale. The probability of the endpoint (death, or any other event of interest, e.g. success) is called the hazard. The hazard is modeled as:

$$H(t) = H_0(t) \times \exp(b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_kX_k)$$

[19] See: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3059453/

where $X_1 \dots X_k$ are a collection of predictor variables and $H_0(t)$ is the baseline hazard at time t, representing the hazard for a person with the value 0 for all the predictor variables. By dividing both sides of the above equation by $H_0(t)$ and taking logarithms, we obtain:

$$\ln\left(\frac{H(t)}{H_0(t)}\right) = b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_kX_k$$

We call $\frac{H(t)}{H_0(t)}$ as the hazard ratio. The coefficients $b_1 \dots b_k$ are estimated by Cox regression, and can be interpreted in a similar manner to that of multiple logistic regression.

In order to simplify the analysis of the Cox regression output, we use the Forward stepwise approach, that is an automatic procedure carrying out the choice of predictive variables. There are various ways that it can be used; however, the general idea is to either start with a large model and keep variables whose p-values are below a certain significance level (backward selection) or to start with a simple model and add variables that have significant p-values (forward selection). Now, we are going to deep dive in these models further:

- Forward Selection chooses a subset of the predictor variables for the final model:
    1) Start with a null model. The null model has no predictors, just one intercept (The mean over Y).
    2) The process searches through all the single-variable models the best one (the one that results in the lowest p-value).
    3) Then it searches through the remaining p-1 variables and find out which variable should be added to the current model to best improve it.
    4) Continue until some stopping rule is satisfied, for example when all remaining variables have a p-value above some threshold.

- Backward Elimination starts from the full model and starts eliminating not significant variables (the least useful predictors) by following some preset criteria.
    1) Start with all variables in the model
    2) Remove the variable with the largest p-value, that is the least statistically significant
    3) The variable with the largest p-value is removed
    4) Continue until a stopping rule is reached, for example when all remaining variables have a significant p-value defined by a threshold.

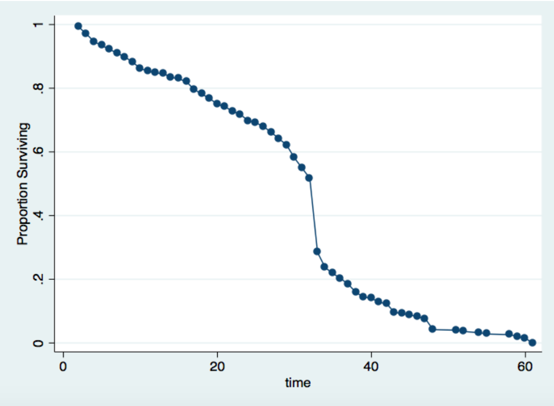
The final step of our analysis will be the use of the interaction model in order to run a supplementary analysis. The standard Cox proportional hazards model has been extended by functionally describable interaction terms. In this way, it allows modelling the influence of one variable in dependence of another variable. This method can be applied to model time dependencies as well as interactions between the covariates. In our context, we will test the relationship between each explanatory variable and each project category in order to study which are the most relevant characteristics within the project categories.

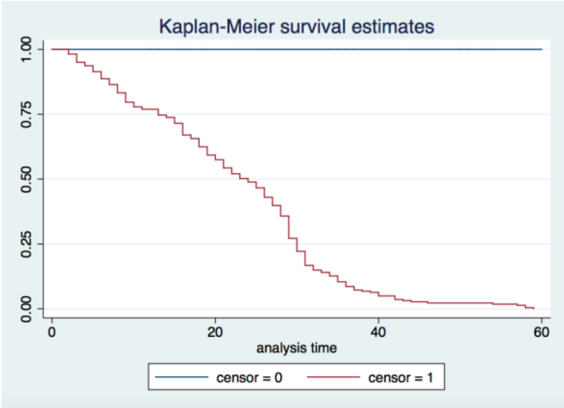
3. Analysis of the *time-to-success* and of its determinants

3.1. Description of the phenomenon

In Figure 9, we can easily have a graphical idea of the dependent variable. As time passes, the probability of not reaching the event – or as we call it, the probability of surviving – decreases. Being a decreasing function, it starts at 1, it continuously diminishes and presents a big jump in the middle of the campaign (around the 30th day) by reaching zero at the end of the campaign (60th day). This is explained by the fact that it is easier to achieve success after many days than at the beginning, because projects have more time for getting the requested funding. We can also understand more about the censor variable, since projects that are successful have probability of surviving that decreases over time, while unsuccessful projects (censor=0) have a probability of surviving that is equal to one, as clearly shown in Figure 9.

Figure 9.
Proportion of surviving and Censor variable

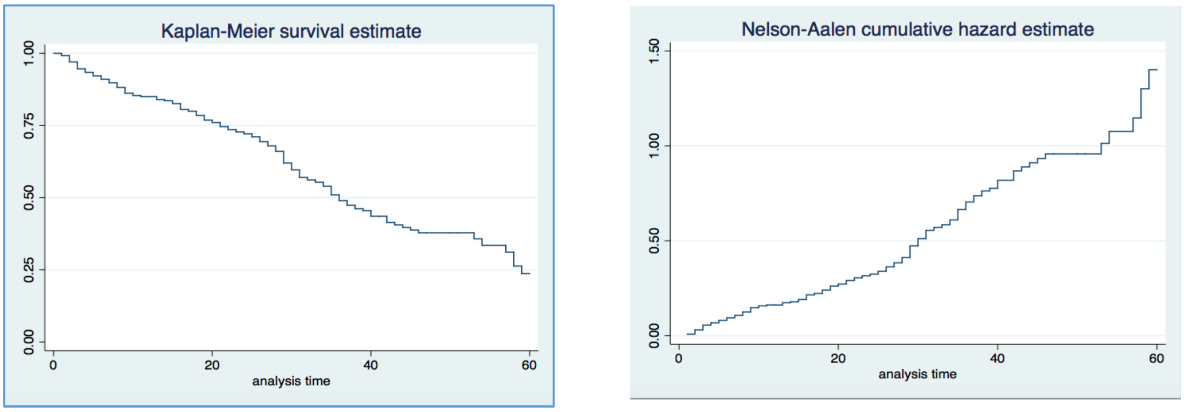




To understand better what we mean by "*survival*", we describe the survival function and the cumulative hazard function. Usually, survival means not experiencing an event, such as death, and it is therefore seen as a positive situation. However, in our case, survival means that the projects are not able to reach the 100% of the funding during the 60 days of the campaign and for this reason they survive. Different from the usual situation, "*death*", is a positive thing in this analysis, since it is seen as "*success*". From Figure 10, it is clear that the probability of surviving is a decreasing function since it starts at 1 at time zero and decreases overtime, as time increases. In particular, the function reaches 25% of surviving at day 60. Regarding the cumulative hazard function, we can say that it expresses the cumulated risk that the event will occur, so it is the probability of "*death*", given a project has survived until that time. In our case, it is the risk that the projects turn into successful ones. It is an increasing function starting at 0 at time zero and increasing as time passes, reaching almost 1.50 at time 60, as it is shown in Figure 10.

From the description of these two functions, we understand that survival and hazard are opposite functions. When projects are able to reach success, their probability of surviving is zero, because they meet the event, and their hazard function is far from zero, since the risk of reaching success is high; and vice versa. To this regard, everything is focused on time, more specifically on the precise day in which the project is able to reach the initial goal that the founders have decided at the beginning of the campaign and the project can be called "*successful*". Since the scope of this analysis is to evaluate the speed of funding for successful projects, we need to understand which factors are relevant for turning the projects into successful ones as fast as possible.

Figure 10.
Kaplan-Meier survival estimate and Nelson-Aalen cumulative hazard estimate

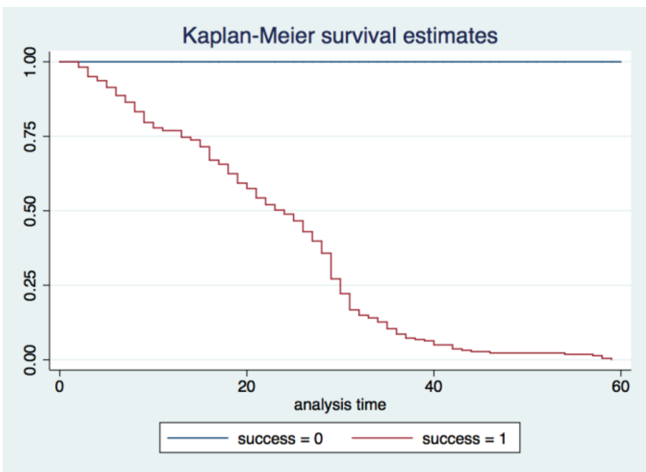


3.2. Univariate Models

The goal of this paper is to use the Cox regression model for studying the relationship between the response variable and the explanatory variables that we have already mentioned and understand which factors are more relevant for the speed of funding of successful projects. However, we first would like to understand the marginal effects; for this reason, we start describing the variables we are interested in by using univariate models, and by studying the relationships between each regressor and the response variable separately. We use two criteria: the log-rank test for binary/qualitative variables, and the Cox regression model for continuous variables. For the latter, we also reclassify them and divide these variables into some ranges (three or four classes) in order to use the log-rank test with the reclassified variables, and to have a graphical idea of the curves.

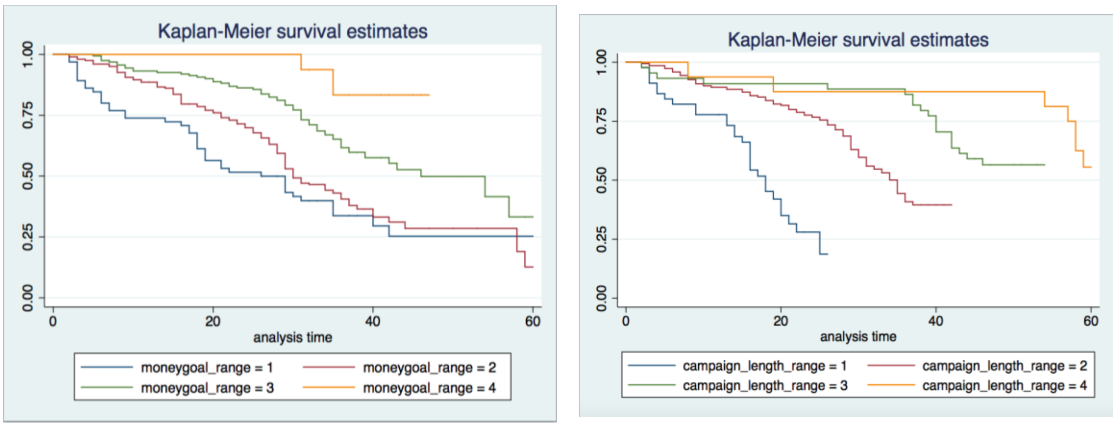
Regarding the log-rank test, we split two groups of projects into successful and unsuccessful ones, we compare the curves, and we look at the significance level of each variable. In technical terms, survival means "*not reaching success*", while the event means that "*the project has achieved success*". To this regard, it seems pretty obvious that unsuccessful projects have a probability of not reaching success that equals to one and therefore they do not reach success, whereas successful projects have a decreasing function of surviving probability, meaning that they are able to reach success throughout the 60days-campaign, as clearly shown in Figure 11. Talking about the second method, the Cox regression model for continuous variables, we analyze what happens to the hazard ratio that the event occurs – meaning the risk that the project becomes successful – when there is an increase of the specific variable. If the hazard ratio increases, it means that the probability of reaching success increases, and vice versa.

Figure 11.
Kaplan-Meier survival estimate for *Success*



First of all, we analyze the *Money_Goal*[20] and the *Campaign_Length*[21]. We can clearly say that with higher money goal the risk of reaching success decreases by a factor of 0.74, meaning that they are characterized by lower speed of achieving success. To be more specific, having a low money goal makes you reach success faster, and having a too high money goal makes the projects unsuccessful. It is advisable to have a money goal lower than $9,750 in order to achieve success (range 1 and range 2). This is explained by the fact that having a really high money goal takes more time to reach success than having a low objective. In terms of campaign length, we can say that with a longer campaign length the risk of reaching success decreases by a factor of 0.90, meaning that speed of reaching success is lower. This result is confirmed if we look at it graphically, since it is recommended to have a campaign length lower than 41 days in order to achieve success faster. It is easy to understand why we have this result: the shorter the campaign, the easier to get the requested funding.

Figure 12.
Kaplan-Meier survival estimate for *Money_Goal* and *Campaign_Length*



Furthermore, our initial results suggest that projects formed by a *Group* and projects formed by an individual are quite similar for the first half of the campaign in terms of probability of reaching success, but then we notice that group projects reach success

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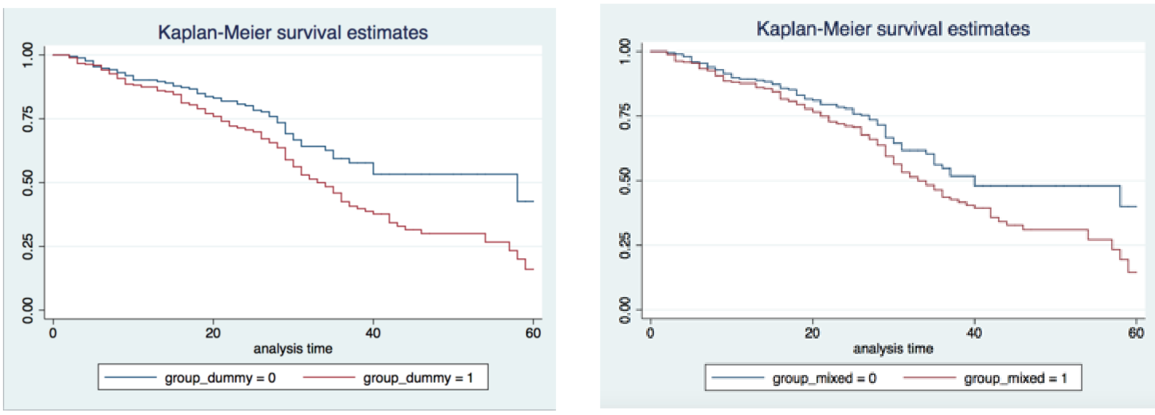
[20] We divide *Money_Goal* in 4 ranges: from 5.29 to 7.19, from 7.2 to 9.1, from 9.2 to 11.1, from 11.2 to 13.1.

[21] We divide *Campaign_Length* in 4 ranges: from 10 to 25, from 26 to 41, from 42 to 56, from 57 to 62.

faster than solo projects. This is explained by the fact that a team brings to the project a larger network size, and also experience in terms of higher degree of specialization, as already anticipated by Mollick (2014). Looking at the *Gender* of the team projects, we clearly see that mixed-gender projects reach success faster than mono-gender projects. This result is expected since an equal balance between males and females brings the right competences into a team. Mixed-gender groups can outperform single-gender teams in speed of funding as they could leverage the activism of female investors who may invest faster (Hoogendoorn et al., 2013).

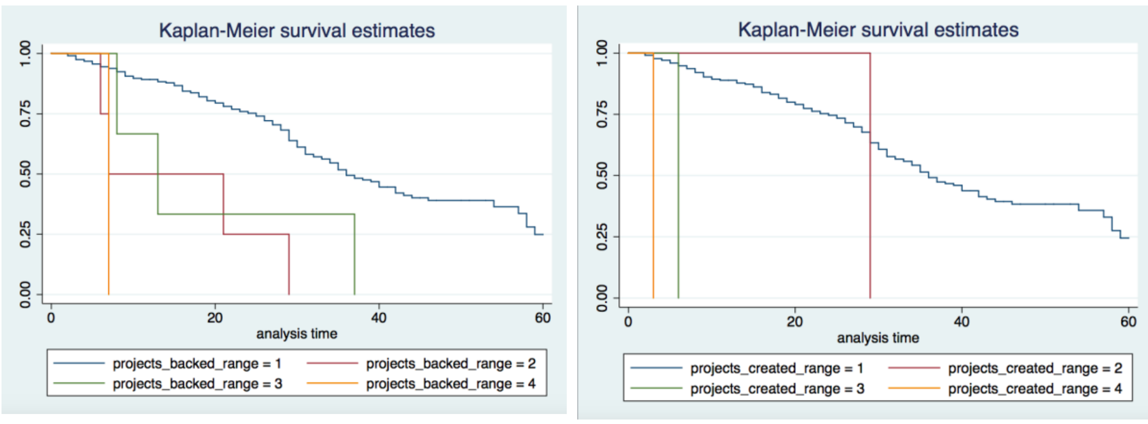
Figure 13.
Kaplan-Meier survival estimate for *Group*, and *Gender* of team projects



If we want to analyze the previous experience of the founders, we look at the number of *Projects_Backed* and *Projects_Created.* In particular, we can say that by having more previous projects backed and created, the probability that the projects turn into successful ones increases by 2.5% for the first one (by a factor of 1.025) and by 4% for the latter one (by a factor of 1.04). To support even more this result, we also consider the number of *Prior_Successful_Projects*, and we clearly notice that, by having more prior successful projects, the probability that the projects turn into successful ones increases by 5% (by a factor of 1.05). To sum up what we have found out, having previous experience, in terms of projects backed, projects created, or percentage of previous successful projects helps the founders replicate success faster in the current project.

In order to see these results graphically, we clearly state that having more *Projects_Backed*[22] increases the probability of reaching success faster; in more details, having more than 26 projects leads to faster success, and if founders have more than 77 previous backed projects, they are able to reach success in less than 30 days. Looking at *Projects_Created*[23], they follow the same thought of projects backed; however, having more than 7 projects leads to faster success (around the 30th day) and if they have more than 16 they need less than 10 days to reach success. Considering the latter variable (*Prior_Successful_Projects)* graphically[24], we can clearly say that having a lot of prior successful projects increases the probability of reaching success; more precisely, having more than 14 prior successful projects leads to reach success in at least half length of the campaign, or faster. This is explained by the fact that entrepreneurs might learn from previous success and already know which factors they should focus on (Piccarreta & Prandelli, 2015).

Figure 14.
Kaplan-Meier survival estimate for *Projects backed, Projects created* and *Prior successful projects*



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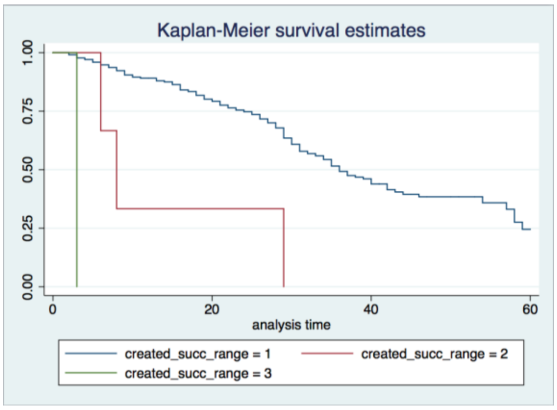
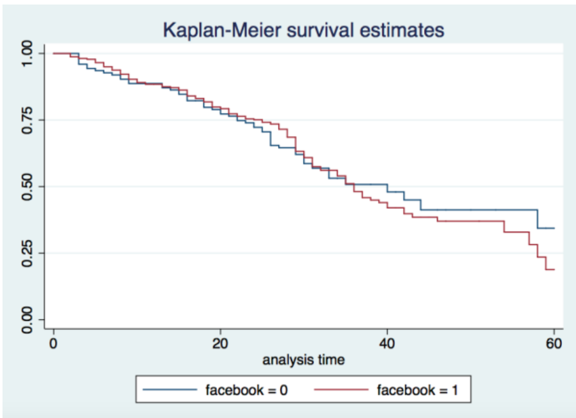
22 For *Projects Backed*, we divide it in 4 ranges: from 0 to 25, from 26 to 51, from 52 to 76, and from 77 to 120.
23 For *Projects_Created*, we divide it in 4 ranges: from 0 to 7, from 8 to 15, from 16 to 23, from 24 to 104.
24 For *Prior_Successful_Projects*, we divide it in 3 ranges: from 0 to 3, from 4 to 14, and from 15 to 88.



Additionally, we study the team capabilities of sharing the project via the social network *Facebook*. Looking at projects with founders registered on Facebook and not, our findings suggest that in the first part of the campaign, it is not clear which one prevails on the other one in terms of probability of reaching success. However, from the middle of the campaign, projects with Facebook reach success faster. This could be explained by the fact that founders, through Facebook, have a bigger network size and can reach a larger number of people. However, we need to take into account that this variable is not statistically significant.

Figure 15.
Kaplan-Meier survival estimate of having *Facebook*



We are going to analyze more characteristics related to the usage of Facebook and in general to the use of communication tools. For an increase of *Facebook_Friends*, the risk that a project turns into a successful one increases by 1.6% (by a factor of 1.63), even if we need to consider that this variable is not statistically significant. Moreover, it turns out that for an increase of *Facebook_Shares*, the risk of reaching success increases again by 2.4% (by a factor of 1.42). Finally, looking at the total number of *Comments* that projects have, we can say that if the comments increase, the probability of being successful increases by 5.2% (by a factor of 1.45). To this extent, we can say that overall the degree of network interaction is really crucial; however, the variable that has the strongest relation with speed of funding is the number of comments on the project's page. This could be explained by the fact that the audience reached with Facebook is really different from the one found on the project's page. While the social network is used for many different reasons and reaches a broader range of different people, people that are actually interested into the project itself visit the project's page.

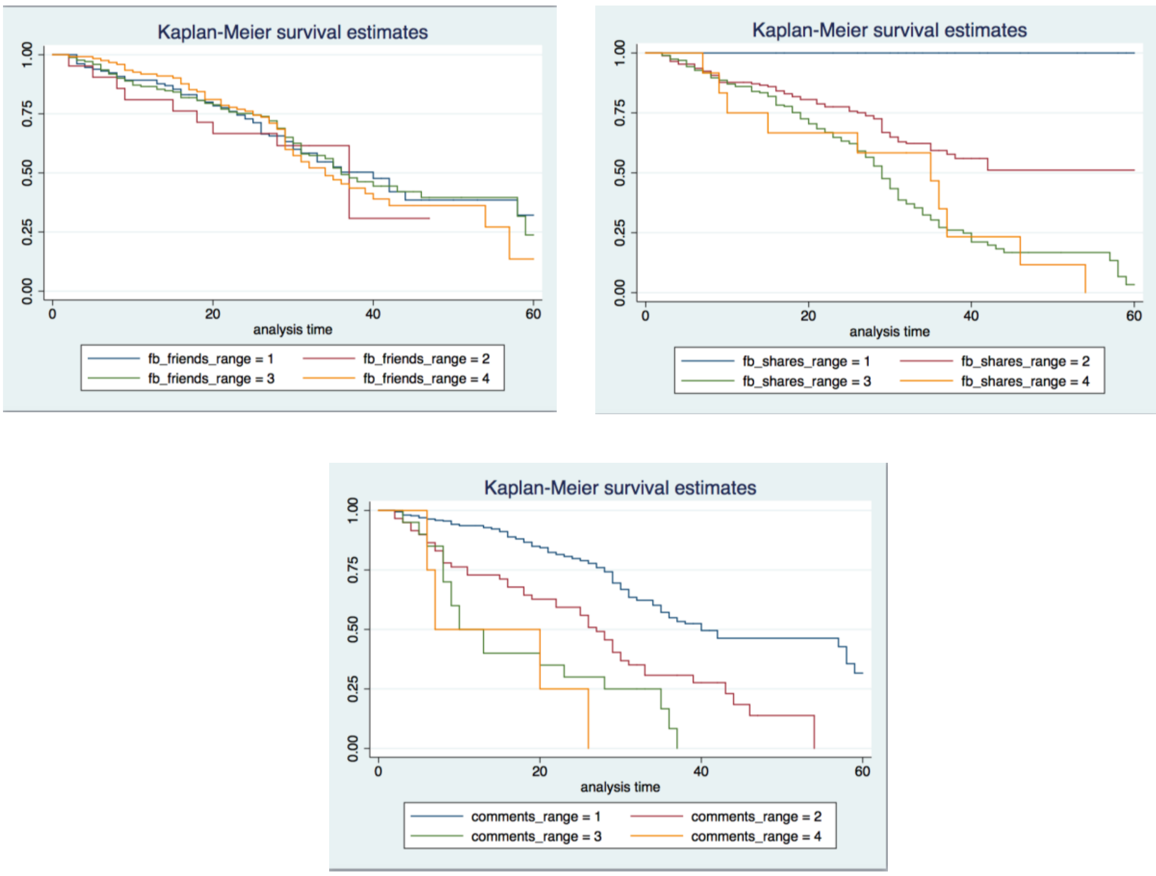
If we look at these three variables reclassified, we have a graphical idea of their association with the depending variable and we understand which is their suggested amount for reaching success. For *Facebook_Friends*[25], there is no clear difference on the number of friends that it is recommended. However, the interesting thing is that projects with a number of friends on Facebook greater than zero and lower than 67 are most likely able to reach success than not having Facebook or having a high number of friends, more than 67 friends. For *Facebook_Shares*[26], we can clearly see in Figure 16 that the ranges of this variable make a difference. In particular, not sharing the project on Facebook leads always to not achieving success, while using a great number of shares brings to success. With the increase of shares on Facebook, projects are faster in reaching success. To have a more precise idea, it is suggested

[25] *Facebook_Friends* is divided into 4 ranges: from 0 to 2.12, from 2.13 to 4.24, from 4.25 to 6.36 and from 6.37 to 8.48.

[26] We divide *Facebook_Shares* into four ranges again: from 0 to 2.61, from 2.62 to 5.23, from 5.24 to 7.85, and from 7.86 to 10.47.

to have more than at least 13 comments per project in order to achieve success (range 3 and range 4). Regarding *Comments*[27] on the projects' page, they follow the same pattern of Facebook shares, meaning that not having comments brings to not achieve success, while having a great amount of comments allows projects to reach success faster, even before the half length of the campaign. With the increase of comments, the probability of reaching success increases; to be more precise, a project should have more than at least 41 projects to be more successful (range 3 and range 4).

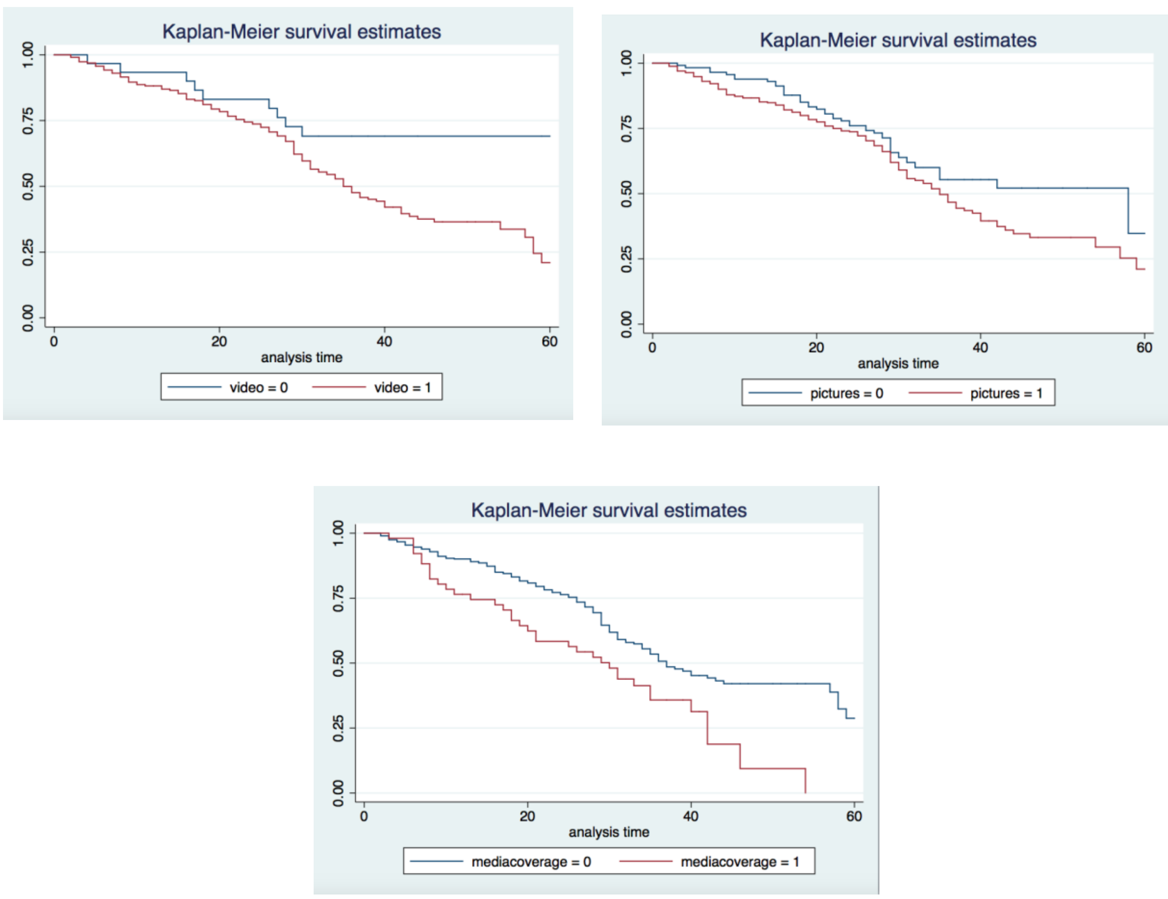
Figure 16.
Kaplan-Meier survival estimate for *Facebook_Friends, Facebook_Shares,* and *Comments*



[27] For *Comments*, we divide the variable in four ranges: from 0 to 1.84, from 1.85 to 3.69, from 3.7 to 5.54, and from 5.54 to 7.38.

Furthermore, we consider the virality of the projects and we start comparing projects that include a *Video*, other media content (*Pictures*), or sponsoring (*Media_Coverage*), and projects that do not have these elements. Our results suggest that having a video brings to higher speed of reaching success, whereas for the other media beside the video there is a weak relationship with *time-to-success* for the first part of the campaign. However, having other media, such as music or pictures, from day 30 to day 60 has a higher probability of reaching success than not including it. Considering whether the project is sponsored by other media or not, we can clearly see that being sponsored on newspapers or websites makes the projects faster to reach success. To conclude, if founders include communication tools in their projects' page, the probability to achieve success will increase, because they are able to make the project more interactive and attract more investors, as already studied by Mollick (2014), and Piccarreta and Prandelli (2015).

Figure 17.
Kaplan-Meier survival estimate for *Video, Pictures,* and *Media_Coverage*



To sum up the results of the univariate models, we can look at the Tables 2a that shows the output of the log rank test of the explanatory variables, and Table 2b for the Cox regression output of the continuous variables.

Table 2a.
Log-rank test output for Binary variables

Variable	Events observed		Events expected		Chi2	Pr>chi2
	0	1	0	1		
Success	0	221	144.37	76.63	444.05	0
Group_dummy	67	154	90.48	130.52	10.57	0.0011
Group_mixed	83	138	101.6	119.4	6.46	0.011
Facebook	59	162	60.87	160.13	0.08	0.7754
Video	9	212	16.08	204.92	3.46	0.0631
Pictures	49	172	60.61	160.39	3.15	0.0757
Media Coverage	185	36	199.06	21.94	10.3	0.0013

Table 2b.
Cox regression output for Continuous variables

Variable	Hazard ratio	Std error	z	P>|z|	[95% Conf Interval]		LR Chi2	Pr>chi2
Money Goal	0.74	0.37	-5.94	0	0.67	0.82	35.78	0
Campaign Length	0.9	0.11	-8.93	0	0.88	0.92	92.32	0
FB friends	1.02	0.24	0.69	0.49	0.97	1.06	0.48	0.49
FB shares	1.42	0.05	9.67	0	1.32	1.53	100.57	0
Comments	1.45	0.06	8.69	0	1.33	1.58	60.55	0
Project backed	1.02	0.005	5.44	0	1.02	1.03	18.18	0
Projects created	1.04	0.009	4.55	0	1.02	1.05	8.74	0.0031
Prior created successful	1.05	0.01	4.41	0	1.03	1.07	8.24	0.0041

3.3. Joint relations of the explanatory variables: Cox Regression

We now study the relationship between the dependent and the whole set of explanatory variables, so as to evaluate the significance of each variable conditioned to all the others. To do so, we use the Cox Regression model described in section 2.2.2.

It is worth mentioning that the coefficients in a Cox Regression model relate to "*hazard*". A positive coefficient indicates the likelihood that the event could happen (meaning increased hazard/risk and decreased survival times) and a negative coefficient indicates that an increase in the variable leads to lower risk that the event could happen. In a simpler way, for an increase of the considered variable, a positive coefficient is translated into more probability that the project turns into a successful one, while a negative coefficient in less probability.

We start analyzing the model with all the baseline variables, namely *Campaign_Length*, *Money_Goal, Group_dummy, Group_Mixed, Video, Pictures, Projects_Created, Projects_Backed, Persucc_Projects_Created, and Facebook*. To this extent, we exclude the variables related to virality, namely *Facebook_Friends*, *Facebook_Shares, Comments and Media_Coverage,* since they have been measured at the end of the projects' campaign. The first comment that it is worth to make is that the most significant variables (with p-value<0.05) are *Campaign_Length, Money_Goal, Projects_Backed, Persucc_Projects_Created, Video, and Pictures.* By decreasing the campaign length and the amount of initial goal, the probability that the project will achieve faster success increases by 0.09% and 7.2% respectively (by a factor of 0.9 and 0.67). These results are in line with what we expected, since they show that the first priority is to set a small amount of money goal with a short campaign length, so that the project can turn into a successful one faster. If founders set a high amount of money goal, the project tends to reach success in a later stage, because it is hard to get to the initial objective set by the founders.

Moreover, with an increase of projects backed in the past and of the percentage of having created a previous successful project, the probability that the success will be delayed decreases by 2.9% and 3.9% (by a factor of 1.03 and 1.64); this means that they significantly reach success faster. This result is expected since being a serial entrepreneur makes a difference, since he might bring more experience into the project, as already examined by Piccarreta and Prandelli (2015). Furthermore, having one more video on the project's page increases the probability of achieving success faster by 13.5% (by a factor of 2.03); this is explained by the fact that the project is more interactive, therefore it attracts more people, and the role of communication tools is significant. Finally, having other media content, apart from the video that we have analyzed before, follows the same reasoning of video. More specifically, if founders include pictures, music, or other content, the probability of reaching success faster increases by 9.9% (by a factor of 1.5).

The next step is to analyze the least significant variable (with p-value<0.20), *Group_dummy.* To this extent, we can say that a project supported by a team has a probability of 3.3% (by a factor of 1.53) to reach success faster than a solo project, since they bring more insights into the work, as already studied previously by Mollick (2014) and Piccarreta and Prandelli (2015). We do not consider the variables with p-values greater than 0.20.

Table 3.
Cox regression model with baseline variables

LR chi2(10) = 186.37
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.9008574	.0108366	-8.68	0.000	.8798664	.9223492
lnmoneygoal	.6717878	.0386261	-6.92	0.000	.600192	.7519241
1.group_dummy	1.533453	.4367852	1.50	0.133	.8774371	2.679938
1.group_mixed	1.30903	.357049	0.99	0.324	.7669676	2.2342
1.video	2.035379	.7125073	2.03	0.042	1.024879	4.042202
1.pictures	1.499075	.2627581	2.31	0.021	1.063224	2.113597
projects_created	1.005797	.0125248	0.46	0.643	.9815462	1.030647
projects_backed	1.029935	.0058863	5.16	0.000	1.018462	1.041537
percsucc_projects_created	1.638792	.4052351	2.00	0.046	1.009349	2.660763
1.facebook	1.085913	.1728593	0.52	0.605	.7948736	1.483516

3.4. Automatic selection of the model: Forward stepwise approach

Since we are dealing with a great number of variables, and more importantly, we notice that some of them are not statistically significant, due to high p-values, we simplify the model by using the *Stepwise* approach, where different combinations of explanatory variables are used to come up with the best model (Woolridge, 2015).

We use the Forward logic by starting from the empty model, meaning the model without regressors. The following step is to find the most significant variable and consequently add the explanatory variables, being among the most significant ones that give the best result together with the previous added variables. In more details, we fit the model by testing the dependent variable *time-to-success* on nothing, then we consider adding the variables ordered by significance levels until the search stops when the level is reached. The first thing to look at is the coefficient of each variable, that explains the relationship between the independent variables and the dependent variable, and it is represented in the third column of the table. If the coefficient is positive, it means that for every increase of the considered variable, we will notice that the probability that the success is delayed (or that *time-to-success* increases) decreases, while the probability that the success happens in shorter time (or that speed of success is faster) increases; for a negative coefficient, vice versa. It is worth to specify that the significance level that we put in the model is 0.2.

Considering the same variables that we analyzed before – only the baseline variables – we can say that the significant variables are *Campaign_Length*, *Projects_Backed, Money_Goal, Group_dummy, Pictures, PerSucc_Projects_Created,* and *Video.* More specifically, we can say that for every unit increase in the length of the campaign, the *time-to-success* increases by 0.1%. This is significantly different from zero, and this result is also expected, since the longer the campaign, the slower the project's speed. Moreover, as we have already seen, with a unit increase of *Projects_Backed,* there is a 2.9% probability that *time-to-success* decreases*.* Having experience in the field allows founders reach success faster because they already have learnt from previous success or also failure. Furthermore, for every unit increase in *Money_Goal*, there is a 7.4% probability that *time-to-success* increases. This result is expected, since it means that if founders set a high amount of money goal, the project tends to reach success in a later stage. Looking at the founders' characteristics, we can say that for every increase in *Group_dummy*, there is a 2.6% chance that *time-to-success* decreases*.* This clearly means that team projects are more likely to reach success in a shorter period than solo projects, as already studied by Mollick (2014), and Piccarreta and Prandelli (2015). Regarding the communication tools, for every unit increase in *Pictures,* there is a 0.9% probability of a *time-to-success* decrease, meaning that if the founders decide to include pictures, videos, or music in the project's page, they are able to achieve success in a shorter period of time. To the same extent, for every unit increase of *Video,* there is a 3.7% probability that *time-*

to-success decreases*.* These two latter results confirm the hypotheses that using communication tools helps founders being successful, since the project becomes more interactive and manages to convince investors to back money on it. Finally, for every increase in *Persucc_Projects_Created,* there is a 1.6% chance of a *time-to-success* decrease*,* since experienced founders in terms of previous successful projects launched on Kickstarter lead to faster success for the current project.

Table 4.
Forward stepwise approach with baseline variables

LR chi2(7) = 184.95
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval	
campaign_length	.9010472	.0106684	-8.80	0.000	.8803782	.9222014
projects_backed	1.029371	.0056264	5.30	0.000	1.018403	1.040458
lnmoneygoal	.674188	.0384468	-6.91	0.000	.6028922	.7539149
group_dummy	1.925773	.2942505	4.29	0.000	1.427397	2.598156
pictures	1.508687	.2600534	2.39	0.017	1.07616	2.115053
percsucc_projects_created	1.716339	.4051056	2.29	0.022	1.080674	2.725908
video	2.037418	.710036	2.04	0.041	1.029054	4.033872

The next step is to add into the model another variable, called *Facebook_Friends,* since we assume that the projects' success does not lead the founder to accept new friends on Facebook. We test the model with the stepwise approach and we realize that there is not any change compared to the previous model. However, we are interested to understand whether the coefficients of *Facebook_Friends* is at least significant in Cox Regression model, due to the fact that it is not considered at all in the stepwise approach. Since it is not statistically significant in either models, we can say that this variable does not have any strong relationship on the model.

Finally, we would like to test the model by including also the variables related to the virality of projects namely *Facebook_Shares, Comments, and Media_Coverage,* and including the above-analyzed *Facebook_Friends*. These variables might be related to the success of the projects, and also, they are measured at the end of the campaign. As a first step, we use the Cox Regression model, but since we are analyzing a large number of variables, we are going to explain their relationship with *time-to-success* by using the Stepwise approach. To this extent, we can say that *time-to-success* can be predicted from the independent variables *Facebook_Shares, Money_Goal, Campaign_Length*, *Comments, Projects_Backed, Group_Mixed, and Video*.

As we have seen before, we can say that for every unit increase in the *Campaign_Length*, there is a 7.4% probability that *time-to-success* increases; and the same for *Money_Goal,* (7.8%). Furthermore, looking at the virality variables, it seems that with an increase in *Facebook_Shares,* there is a 5.9% probability of a decrease in *time-to-success*, and to the same extent, by having more comments on the project's page (with a unit increase of *Comments)*, there is a 2.3% probability that *time-to-success* decreases, meaning that founders should attract investors on their project's page so that they are motivated to comment the project with questions, observations, or feedback. This could be made even easier through *Facebook_Shares*, in which founders try to reach as many people as possible and to attract investors on the platform. In addition, it is interesting to notice that the variable *Group_Mixed* enters into the game, since if the team is composed of a mixed gender, the probability that it reaches success faster increases by 9.3% compared to mono-gender teams. Finally, as already anticipated, *Projects_Backed* and *Video* play a significant role, since with an increase in projects backed, there is a 1.9% probability that *time-to-success* decreases; to a less extent, with the presence of a *Video*, 0.1% probability that they reach success faster.

Table 5.
Forward stepwise approach with all variables

LR chi2(7) = 438.27
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_fb_sharesplus1	2.058582	.1306205	11.38	0.000	1.817849	2.331193
lnmoneygoal	.3783305	.0293294	-12.54	0.000	.3250001	.4404121
campaign_length	.8735344	.010948	-10.79	0.000	.852338	.8952579
ln_comments_plus1	1.523352	.1016607	6.31	0.000	1.336581	1.736221
projects_backed	1.018688	.0060908	3.10	0.002	1.00682	1.030696
group_mixed	1.293451	.1912181	1.74	0.082	.9680821	1.728176
video	1.600925	.5612211	1.34	0.179	.8053292	3.182502

We would like to compare the first model that includes only baseline variables – excluding virality variables – with the second one that considers all explanatory variables. Clearly, we can say that some variables, such as *Campaign_Length, Money_Goal, Projects_Backed,* and *Video,* have a crucial role in both models. On the one hand, founders should take into account the importance of establishing the right length of the campaign (considering that the maximum number of days is 60) and setting the right amount of money goal. As Mollick (2014), and Kuppuswamy and Bayus (2015) already said, the amount of funding decided at the beginning of the campaign is related to projects' success, the lower it is, the most likely the success. Following his result, we have noticed that it is also related to the speed of success. To this extent, having a short campaign length and a relatively low money goal (of course, it depends on the involved project) can lead to faster success. On the other hand, speed of funding is driven by the past experience of the founders, in terms of projects that they have previously backed. As the existing literature teaches us (Colombo, 2005; Hsu, 2007; Dencker et al., 2009; Gompers et al., 2010; Ahlers et al., 2015; and, Piccarreta & Prandelli, 2015), past success is a signal of quality and reliability that can overcome some of the information asymmetries that are natural in the crowdfunding setting. To this extent, we can say that previous experience on Kickstarter can help founders to manage the current project more easily and faster, since they already now the challenges and problems from past success or failure. However, at this stage, previous experience is thought only as number of projects supported. Finally, we should say that the presence of video plays a crucial role into driving speed of funding. As we have already seen in the literature (Piccarreta & Prandelli, 2015), having communication and marketing tools allows the founders to be most likely successful; now we can add that they will be able to reach success in a faster way, because the project is more interactive and attracts more people.

We can start depicting the differences between the two models. On the one hand, the first model considers as important the team composition, the previous successful experience and the presence of communication tools, such as video and other media content. Looking at the characteristics that the team should have, it is faster to reach success when founders start a team project than solo projects. The relationship between having a group and being successful has already been shown in the existing literature, and our results demonstrate that there is also a relationship between groups and speed of funding. More entrepreneurs can bring experiences, skills, and advices into the current project, since larger teams have a higher degree of internal specialization (Piccarreta & Prandelli, 2015). In addition, Mollick (2014) finds out that group projects are more likely to be successful than projects run by a single person, since personal networks are highly correlated with crowdfunding efforts. Additionally, we clearly notice that the importance of previous experience is also studied in terms of the percentage of past successful projects. It is not only about the number of projects that the founders have backed in the past, but also, how many projects they created that have been successful (referring to the percentage of successful projects). This result is expected, since Piccarreta and Prandelli (2015) have already studied the crucial role that previous created projects play; the experience of serial founders might help the project to find the right amount of funding for being successful faster (Hsu, 2007; Dencker et al., 2009; Gompers et al., 2010; Ahlers et al., 2015). Furthermore, we have seen that the presence of interactive tools is important, but in the first model we notice that it is not only suggested the presence of video, but also other media content in terms of music, pictures, or another video. As already seen in the existing literature (Mollick, 2014, and Piccarreta & Prandelli, 2015), communication and marketing tools might attract people on the projects' page and convince investors that the project is a great idea to invest in. In these terms, having both videos, and other media, allows to reach success faster.

On the other hand, talking about the model in which we decide to include virality variables, we clearly see that speed of funding is clearly driven by the presence of comments on the project's page, the shares on Facebook, and the gender of the team. In order to reach success faster, founders should attract people and make them comment on the page of the project in a way that they can ask questions, share their thoughts and give feedback. This behavior is driven by sharing the project on Facebook, in order to reach a broader audience and convince people to visit the page on Kickstarter. As already studied by Mollick (2014), the role of social networks in funding new ventures has been noted as important. Learning how to use them effectively can take to success faster. In addition, since in this model previous experience is seen only as number of projects backed, and not as percentage of previous successful projects, we can clearly say that using communication and interactive tools seems to be more important than having previous successful experiences. Interestingly, adding the virality variables into the model makes important the gender within the team. In the existing literature, it is not clear whether it is suggested to have a mono-gender or mixed-gender teams (Hoogendoorn et al., 2013), but it seems that having a mixed-gender team allows to reach success faster, since men and women have differentiated skills and mindsets; the team needs both of them in order to be successful.

To sum up the previous results, we can say that some variables have proved to be consistent among the models. The two models share the importance of structural characteristics, such as *Campaign_Length*, and *Money_Goal*, and this is followed by the fundamental role of having previous experience in terms of *Projects_Backed* and the presence of a *Video*. Talking about the differences, speed is driven by the presence of a *Group*, together with previous experience seen as the *Percentage of previous successful projects*, and by interactive tools, such as *Pictures* and other media content. However, introducing the variables that have been measured at the end of the campaign and might be related to the success per se, *Comments, Facebook_Shares,* and *Gender_Group* play a crucial role in driving the speed of funding.

Nevertheless, it is worth mentioning that some initial propositions are not confirmed, because some variables do not play a crucial role in our analysis. Even if we have seen that the presence of interactive and communication tools is crucial in driving speed of funding, *Media_Coverage* is not considered as relevant as we expected. Sponsoring the project on other websites and other newspapers does not help the founders to find the requested funding; it might be that having videos and other media content is enough, and the role of social networks is more effective than newspapers or websites. Finally, the presence of *Facebook* and the number of *Facebook_Friends* do not have a strong relation with speed of funding. Even if Mollick (2014) finds out that a signal of a large social network (high number of Facebook friends) is associated to more successful campaigns but a signal of a small social network is worse than no signal at all, Facebook friends does not seem to be related to speed of funding. This could be related to the fact that Facebook is used for different reasons, and its primary goal is not to fund projects. If someone is really interested in invest in projects, he/she visits the right websites and platforms to do so. The number of friends is not indicative, since a founder might have a lot of friends, but not interested in investing money. Having Facebook per se does not lead to reach success faster, but, since we have seen that *Facebook_Shares* is crucial, it is a necessary condition for sharing the project on this social network.

4. Supplementary Analysis

4.1. Interaction Model

After having depicted what drives the speed of funding, we would like to deep dive into the model and understand whether project and team characteristics, and team capabilities are more relevant in some project categories. In order to do that, we use the Interaction Model in which we first include the categories to the simplified model seen in Section 3.4, and then we study the relation of each explanatory variable and the *time-to-success* within the project category through the interactions. In this way, we analyze the importance of each variable across project categories. However, before starting, we would like to state that we run this analysis only with baseline variables, excluding *Facebook_Friends, Facebook_Shares, Comments, and Media_Coverage*, because as already said they might be related to the success of the project itself.

4.1.1. Simplified model including project categories

We first test the model by considering only baseline variables that have resulted significant in the stepwise approach and we add the categories *Art, Comics, Dance, Design, Fashion, Film&Video, Food, Games, Music, Photography, Publishing, Technology, and Theatre*. At this stage, we can verify whether some categories are advantaged compared to the other ones. It seems that *Fashion, Games, Film&Video,* and *Food* (with $p\text{-value}<0.10$) and to a lesser extent *Technology* (with $p\text{-value}<0.20$) present some advantages compared to the other categories. However, even if these categories are the most significant ones, we would like to deep dive and test the model with all the categories anyway.

Table 6.
Simplified model including project categories

LR chi2(12) = 214.42
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8984213	.0108084	-8.90	0.000	.877485	.9198571
projects_backed	1.035288	.0062222	5.77	0.000	1.023164	1.047556
lnmoneygoal	.6911825	.0401853	-6.35	0.000	.6167425	.7746072
group_dummy	2.235991	.3549505	5.07	0.000	1.638124	3.052062
fashion	.1953128	.0996045	-3.20	0.001	.0718852	.5306664
pictures	1.577973	.2736615	2.63	0.009	1.123257	2.216767
games	.4200722	.1246794	-2.92	0.003	.234792	.7515616
percsucc_projects_created	1.562664	.3703364	1.88	0.060	.9820619	2.486521
film_video	.6692756	.1192003	-2.25	0.024	.4720663	.9488704
video	1.912851	.6725239	1.84	0.065	.9603156	3.810204
food	.5740217	.1842082	-1.73	0.084	.3060348	1.076678
technology	.5114012	.2612775	-1.31	0.189	.1878791	1.392018

4.1.2. Simplified model including categories and interactions

In this section, we use the model analyzed in Section 4.1.1 and we add the interactions among the different project categories and the significant variables. In this way, we will be able to see whether each variable has a different relationship with speed of funding depending on the project category considered. We need to take into account that an explanatory analysis showed the presence of multicollinearity problem in this model[28], therefore we decided to remove some interactions. Clearly, we can say from Table 7 that the most significant variables

[28] See supplementary analysis in Appendices.

(with pvalue<0.005) are *Food_video, Fashion_goal, Food_pictures, Games_goal, Film_pictures, Design_Percsucc_Projects_created,* and to a lesser extent *Comics_backed, Comics_group,* and *Technology_campaign* (with p-value<0.15).

In order to see the relations between each variable and speed of funding among the different categories, we can say that *Video* is not a driver of speed of funding in the *Food* category. In fact, with an increase in *Video,* meaning that the video is present in the campaign, there is a probability of 1.8% that the *time-to-success* increases. Conversely, including other media content (*Pictures)*, apart from videos, increases the probability that the *time-to-success* decreases by 2.3%. This means that including videos in the *Food* category does not make the success faster, while the presence of other media content does. This could be explained by the fact that in order to convince people to invest in a new product related to *Food* faster, the project should attract investors' attention through the use of a good picture or image, but it does not need a video. Comparing *Pictures* among categories, we see that this variable is really important in *Film&Video*, but in the opposite direction, since with an increase in *Pictures,* there is a 2.5% probability that the success is delayed. This is pretty straightforward, since pictures are not enough when launching a film or video project: it is impossible to get an idea of these kind of projects through pictures, so maybe founders should include something more attractive to get the initial funding, such as videos. The latter is only an assumption because we do not see it as a result from our analysis.

Talking about the *Money_Goal* that entrepreneurs set at the beginning of the campaign, it turns to be really important in *Fashion* and *Games*, since with an increase in the amount of goal, there are probabilities of 3% and 0.1% that *time-to-success* increases. This means that setting a low money goal allow founders to reach success faster in both *Fashion* and *Games*, but especially in the *Fashion* industry. This explained by the fact that *Fashion* evolves so quickly, that people want to have the real project as soon as possible. Furthermore, if we analyze the *Percentage of* *previous successful projects created*, we can say that it is really relevant in *Design*, since with a higher percentage of previous successful projects, the probability that *time-to-success* decreases is 4.8%, meaning that previous experience helps entrepreneurs to get the initial funding faster. This could be explained by the fact that it is quite rare to found a *Design* project, so having some experience might be helpful.

To a lesser extent, we can say that *Project_Backed* is relevant in *Comics*, meaning that having supported more projects in the past, increases the probability of getting the funding faster by 7%. Still in *Comics* category, having a *Group* does not help getting the funding faster, since when there is a group, the probability that success is delayed is 8.5%. So, for the *Comics* projects, it is better to be a solo founder, since the only thing needed is creativity, and to have supported some projects in the past. Finally, looking at the *Campaign_Length,* we can clearly say that having a longer campaign length will decrease the probability of getting the funding by 7.7%, meaning that people founding projects related to *Technology* should consider that in order to achieve success, they need to have a short campaign length. This could be explained by the fact that we are surrounded by advanced technologies every day, and new applications are born very often. The world is really dynamic, therefore it is important to be quick and anticipate customers' needs.

To sum up the previous results, we can clearly say that the project categories in which the driving factors resulting important are *Food, Film&Video, Games, Fashion* - as expected since they are advantaged - and *Design, Comics,* and *Technology*. We can clearly say that these categories can be easily split in two broad branches. On the one hand, we have the ones that share the pattern of being a multimedia category, meaning that they use a combination of different content forms, such as text, audio, images, animations, video, and interactive content (*Film&Video, Games, Comics,* and *Technology*). On the other hand, we have categories that follow the "*trends*", and reflect how the modern society is evolving in new lifestyles, and behaviors, such as *Food, Fashion,* and *Design.* Above all, we can say that the supplementary analysis allows us to draw conclusions that are consistent with the general results of this thesis. It seems that the factors affecting the speed of funding the most among project categories resume the idea that in order to get the funding faster, founders need to be careful with the structural characteristics of the project, meaning setting the right amount of money goal and the right campaign length. In addition to that, entrepreneurs should include interactive tools, but depending on the category in which they are launching the project in, videos or pictures are more or less appropriate. Finally, having more previous successful experience always helps the founders to achieve success faster, especially in the categories that have a lower number of projects.

Table 7.
Final simplified model including categories and relevant interactions

LR chi2(16) = 235.69
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8961827	.0106817	-9.20	0.000	.8754895	.9173649
projects_backed	1.036811	.006626	5.66	0.000	1.023905	1.049879
lnmoneygoal	.6965262	.0405257	-6.22	0.000	.6214587	.7806611
group_dummy	2.379631	.3787301	5.45	0.000	1.741954	3.250742
design_percsucc	**21.74825**	**23.47375**	**2.85**	**0.004**	**2.622338**	**180.3682**
fash_goal	**.830093**	**.0470263**	**-3.29**	**0.001**	**.742856**	**.9275747**
pictures	1.785876	.3197049	3.24	0.001	1.257392	2.536485
games_goal	**.900702**	**.0312033**	**-3.02**	**0.003**	**.8415748**	**.9639834**
film_pictures	**.5247066**	**.1154576**	**-2.93**	**0.003**	**.3408916**	**.807638**
food_video	**.0184224**	**.0201883**	**-3.64**	**0.000**	**.0021506**	**.1578122**
food_pictures	**29.0232**	**30.55918**	**3.20**	**0.001**	**3.685496**	**228.557**

video	1.999176	.7426492	1.86	0.062	.9652698	4.140506
percsucc_projects_created	1.360631	.3477028	1.21	0.228	.8245558	2.245231
technology_campaign	**.9775788**	**.0147324**	**-1.50**	**0.132**	**.9491261**	**1.006885**
comics_group	**.1854649**	**.1372024**	**-2.28**	**0.023**	**.0435074**	**.7906054**
comics_backed	**1.070877**	**.0304873**	**2.41**	**0.016**	**1.012759**	**1.132329**

5. Discussion

5.1. Conclusions and implications for entrepreneurs

The results of this exploratory analysis have been confirming some evidence proved by the existing literature in terms of the factors that drive success in crowdfunding and extended it to another relevant performance indicator such as speed of funding. In light of the relationships we showed through the use of a sample of 500 Kickstarter projects, entrepreneurs can take more informed decisions on three main layers. The first one are the structural projects' characteristics: before launching the campaign on Kickstarter, founders need to decide the right amount of money goal and the right length of the campaign. As studied by previous researchers (Mollick, 2014), such features are strictly related to the success of the project on the platform, since the probability of being successful is driven by low money goal and short campaign length. We proved that they are also linked to the speed of funding, meaning that projects with appropriate goals and the right schedule raise money faster and signal that founders are able to deliver a product on time or even faster.

The second decision is about signaling the right founders' characteristics when starting a new project. From this topic, we have found out several results. Founding the project within a team increases the probability of reaching success faster than being a solo founder. This result confirms what has been seen by the existing literature (Mollick, 2014; Piccarreta & Prandelli, 2015), since they have studied the impact of networks on projects' success: personal networks are highly correlated with crowdfunding efforts. Furthermore, group projects are more likely to be successful, since larger teams have a higher degree of internal specialization and each member could have differentiated skills. To further extend these thoughts, we have found out that being in a group allows for reaching success faster, since entrepreneurs might have different backgrounds, skills, and experiences to bring into the venture. We also find out that a mixed-gender group might help to reach success faster due to internal diversity, consistently with literature in other contexts (Hoogendoorn et al. 2013; Vogel, Wester, Hammer & Downing-Matibag, 2014). Furthermore, we analyzed whether the group that has already had previous experience in crowdfunding is faster at being successful again. According to the existing literature (Dencker, et al., 2009), having previous experience increases the probability of reaching success; moreover, successful prior experience has been shown to be a determinant of success for entrepreneurial ventures (Hsu, 2007; Gompers et al., 2010; Ahlers et al., 2015; and, Piccarreta & Prandelli, 2015). We prove that speed of funding is driven by previous experience of the founders, especially in terms of previous projects backed. However, we also see that previous successful experience helps in achieving success faster; this is explained by the fact that entrepreneurs have learnt from previous success (Minniti & Bygrave, 2001).

The third decision that entrepreneurs need to take is what kind of team capabilities the entrepreneurs need to have in order to be successful faster. First, it is important to work on the network size and its degree of interaction, and the role of social networks in funding new ventures has also been noted as being really important (Mollick, 2014). We use Facebook as the representative tool for studying the network size, and we confirm that being active on this social network definitely helps founder to achieve success faster. In particular, if the founders share the project on Facebook and have a high degree of interaction, they attract people making them curious about knowing more about the new project. This behavior leads to have more comments on the Kickstarter project's page posted by individual backers, and success is reached in a quicker and more efficient way. In addition, entrepreneurs need to develop their skills in using marketing and communication tools; indeed, we prove that they are important drivers of the speed of funding. Videos and other media content, such as images, music or other interactive tools have a strong relationship with the speed of funding in the sense that their presence make projects much faster to reach their goal. In this way, the project seems to be more interactive and investors are more willing to send their money right away to the new project.

As a final step, these factors have also been studied also across different project categories through a supplementary analysis, and we are able to see the different relationships that they have depending on the project category founded. Hence, overall, founders that would like to increase the chances of supporting their ventures with reward-based crowdfunding, and to increase the speed of receiving the funding from investors, should pay attention to signal particular project features associated to fast success achievement. The most important implication is that entrepreneurs need to carefully decide which goals they want to achieve in a realistic way.

Don't be too ambitious, set the goals that you are sure to achieve.
Ambition is one of the positive qualities of entrepreneurs; however, in this field it is important that they are also realistic. As already mentioned before, it is all about the amount of funding that the founders decide at the beginning of the campaign, and also the length of the campaign that they set. It is rare that they are able to overcome the initial money goal, meaning that these two structural features are the most important decisions that they need to make. Delivering the project on time, and faster than expected, is more valuable to both the founders, that feel even more motivated, and to the investors, that are satisfied with their funding, and they are more likely to invest in the next project.

It is not only about the project idea that you have, but also whether to start the project with someone else or not.

When having an idea to test in the market, the first thing that entrepreneurs need to decide is who to start the project with, alone or with someone else. It might be considered a low-priority decision to take, but the team is the main driver of funding from an investors' point of view. If entrepreneurs want to reach success faster, it means that they need to reach the 100% of the funding, meaning that they need to convince the investors to back into the project as soon as possible. This could also be speeded up with the right team in place. People with different backgrounds, skills, and experiences will form the perfect match for reaching success faster. Supporting even more the fact that founders' experience is crucial, entrepreneurs should take into account that having previous experience in the field helps to reach success faster. This is explained by the fact that these entrepreneurs have already learnt from previous failures and successes. In fact, regarding the latter, if founders have previous successful experience, this leads them to achieve success even faster.

It is not enough to have communication tools and social networks, but you need to understand how to use them.

To reach crowdfunding success, it is therefore important to reach the "*crowd*" and to attract a high number of investors. However, the best way to reach this result is being as much interactive as possible. This means that it is not sufficient to only be present on social networks as the key driver is being active on them. Clearly, there are different ways of doing so, but using Facebook in the right way helps to reach success faster; entrepreneurs need to understand that sharing the project on Facebook attracts investors, since curiosity takes them to the description of the project and makes them comment on the project's page with feedback, questions, or observations. This behavior makes the project viral and convinces investors to fund the project. To support this even more, founders need to make the project's page interesting and attractive; one way of doing so is to include videos, music, images, and other enriching content, so that investors will remember more easily the main characteristics of the project.

Be always motivated and follow your entrepreneurial mind. Don't stop at the first project you are successful in.

The main thing that entrepreneurs need to keep in mind is that passion is the main driver of success; in order to reach success, founders have to believe in their ideas. Motivation is mostly something that is internally stimulated (Bassett-Jones & Lloyd, 2005) and it should be aligned with the team goals; once the team has clear goals in mind, it can reach success faster. But more importantly, being successful once should not stop the founders at achieving success again, rather it should make them start and believe in other ideas and projects they have in mind.

5.2. Limitations and suggestions for future research

In this section we will outline the limitations of our study and we will give some insights for future research. First of all, the study has been focusing only on data gathered from the platform Kickstarter, which is characterized by an "*all-or-nothing*" scheme. It would be interesting to study how the relationships highlighted in this study change in a setting where the incentives to pledge are less structured. Another boundary condition is the setting of reward-based crowdfunding. It may be possible that equity-based crowdfunding would work differently because of the more traditional investment logic and speed of funding is not as strongly related as in reward-based crowdfunding. Also, donation-based crowdfunding can be different too as the speed of funding can be influenced by other factors that are not directly related to the founders but maybe the context where donation takes place. Future studies could also analyze other types of crowdfunding in order to be able to talk about crowdfunding in general.

While the amount of data that could be collected on the platform is extensive, because of time constraints we are not able to gather all types of information, so another possible way of extending this work is to broaden the dataset. We do not collect data on the background, competences, experiences of the founders, and this could be an extensive area of research that could be added to this paper. In relation to the network effect, we only considered the number of Facebook shares and comments without considering and analyzing the quality of them, so future research could improve this part by selecting only the relevant information.

Considering the limitations in terms of type of variables used, some variables that vary with time are baseline and they are taken at the beginning or at the end of the campaign, while it would be interesting to see how they changed throughout the campaign and monitor them. In particular, it is important to underline that the indicators related to virality could not be tracked on a granular basis along the whole campaign period and the information gathered specifically refers to the measurements taken at the end of the campaign. For this reason, it is not possible to properly study the impact of virality gained at a given stage on the performance of the projects in the subsequent periods. To this extent, future research might extend further this study and analyze what drives the speed of funding in different phases of the campaign. This means collecting information of the variables every day of the campaign or in specific periods and see whether there are relevant differences.

Even if this paper presents several limitations, it has contributed by giving useful insights to future researchers in terms of factors that affect the speed of funding for successful projects and also to give some advices to entrepreneurs. Clearly, these results could be investigated and extended in order to understand what drives the crowd throughout the campaign.

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Appendices

Table 8.
Time throughout the campaign

Interval		Beg. Total	Deaths	Lost	Survival	Std. Error	[95% Conf. Int.]	
2	3	444	4	0	0.9910	0.0045	0.9762	0.9966
3	4	440	7	0	0.9752	0.0074	0.9557	0.9862
4	5	433	3	0	0.9685	0.0083	0.9473	0.9812
5	6	430	5	0	0.9572	0.0096	0.9337	0.9725
6	7	425	6	0	0.9437	0.0109	0.9178	0.9616
7	8	419	5	0	0.9324	0.0119	0.9048	0.9523
8	9	414	7	0	0.9167	0.0131	0.8868	0.9389
9	10	407	8	0	0.8986	0.0143	0.8666	0.9233
10	11	399	4	0	0.8896	0.0149	0.8566	0.9154
11	12	395	2	0	0.8851	0.0151	0.8517	0.9115
12	13	393	1	0	0.8829	0.0153	0.8492	0.9095
13	14	392	6	0	0.8694	0.0160	0.8343	0.8974
14	15	386	2	0	0.8649	0.0162	0.8294	0.8934
15	16	384	5	0	0.8536	0.0168	0.8172	0.8833
16	17	379	12	0	0.8266	0.0180	0.7880	0.8587
17	18	367	7	0	0.8108	0.0186	0.7712	0.8443
18	19	360	7	0	0.7950	0.0192	0.7544	0.8297
19	20	353	8	0	0.7770	0.0198	0.7354	0.8130
20	21	345	4	0	0.7680	0.0200	0.7259	0.8046
21	22	341	7	0	0.7523	0.0205	0.7094	0.7898
22	23	334	5	0	0.7410	0.0208	0.6976	0.7792
23	24	329	9	0	0.7207	0.0213	0.6765	0.7600
24	25	320	3	0	0.7140	0.0214	0.6695	0.7536
25	26	317	6	0	0.7005	0.0217	0.6555	0.7407
26	27	311	9	0	0.6802	0.0221	0.6346	0.7214
27	28	302	10	0	0.6577	0.0225	0.6115	0.6997

28	29	292	10	0	0.6351	0.0228	0.5885	0.6780
29	30	282	20	0	0.5901	0.0233	0.5428	0.6342
30	31	262	16	0	0.5541	0.0236	0.5066	0.5989
31	32	246	16	0	0.5180	0.0237	0.4705	0.5633
32	33	230	107	0	0.2770	0.0212	0.2362	0.3192
33	34	123	18	0	0.2365	0.0202	0.1981	0.2769
34	35	105	8	0	0.2185	0.0196	0.1813	0.2580
35	36	97	6	0	0.2050	0.0192	0.1688	0.2437
36	37	91	8	0	0.1869	0.0185	0.1522	0.2245
37	38	83	12	0	0.1599	0.0174	0.1276	0.1956
38	39	71	6	0	0.1464	0.0168	0.1154	0.1810
39	40	65	2	0	0.1419	0.0166	0.1113	0.1761
40	41	63	6	0	0.1284	0.0159	0.0993	0.1614
41	42	57	3	0	0.1216	0.0155	0.0933	0.1539
42	43	54	12	0	0.0946	0.0139	0.0697	0.1240
43	44	42	1	0	0.0923	0.0137	0.0677	0.1215
44	45	41	2	0	0.0878	0.0134	0.0638	0.1165
45	46	39	2	0	0.0833	0.0131	0.0600	0.1114
46	47	37	3	0	0.0766	0.0126	0.0543	0.1037
47	48	34	16	0	0.0405	0.0094	0.0249	0.0618
50	51	18	1	0	0.0383	0.0091	0.0232	0.0591
51	52	17	1	0	0.0360	0.0088	0.0215	0.0564
53	54	16	1	0	0.0338	0.0086	0.0198	0.0537
54	55	15	2	0	0.0293	0.0080	0.0164	0.0481
57	58	13	1	0	0.0270	0.0077	0.0148	0.0453
58	59	12	3	0	0.0203	0.0067	0.0100	0.0368
59	60	9	3	0	0.0135	0.0055	0.0056	0.0279
60	61	6	6	0	0.0000	.	.	.

Table 9.
Log-rank test for equality of survivor functions for *Success*

chi2(1) = 444.05
Pr>chi2 = 0.0000

Success	Events observed	Events expected
0	0	144.37
1	221	76.63
Total	**221**	**221.00**

Table 10.
Cox regression for *Money_Goal*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761

Log likelihood = -1211.0572

Number of obs = 444

LR chi2(1) = 35.78
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
lnmoneygoal	.7413241	.037372	-5.94	0.000	.6715788	.8183128

Table 11.
Cox regression for *Campaign_Length*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761

Log likelihood = -1182.7903

Number of obs = 444

LR chi2(1) = 92.32
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8972986	.0108883	-8.93	0.000	.8762097	.9188952

Table 12.
Log-rank test for equality of survivor functions for *Group*

chi2(1) = 10.57
Pr>chi2 = 0.0011

Group_dummy	Events observed	Events expected
0	67	90.48
1	154	130.52
Total	**221**	**221.00**

Table 13.
Log-rank test for equality of survivor functions for *Gender* of the team

chi2(1) = 6.46
Pr>chi2 = 0.0110

Group_mixed	Events observed	Events expected
0	83	101.60
1	138	119.40
Total	**221**	**221.00**

Table 14.
Cox regression for *Projects_Created*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761

Log likelihood = -1224.5778

Number of obs = 444

LR chi2(1) = 8.74
Prob > chi2 = 0.0031

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
projects_created	1.040611	.0091118	4.55	0.000	1.022905	1.058624

Table 15.
Cox regression for *Projects_Backed*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(1) = 18.18
Log likelihood = -1219.8594 Prob > chi2 = 0.0000

_t	Haz.Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
projects_backed	1.025399	.0047239	5.44	0.000	1.016182	1.0347

Table 16.
Cox regression for *Ncreated_Successful*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(1) = 8.24
Log likelihood = -1224.8296 Prob > chi2 = 0.0041

_t	Haz. Ratio.	Std. Err.	z	P>z	[95% Conf. Interval]	
ncreated_succ	1.047504	.0110272	4.41	0.000	1.026112	1.069341

Table 17.
Log-rank test for equality of survivor functions for *Facebook*

chi2(1) = 0.08
Pr>chi2 = 0.7754

Facebook	Events observed	Events expected
0	59	60.87
1	162	160.13
Total	**221**	**221.00**

Table 18.
Cox regression for *Facebook_Friends*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761
LR chi2(1) = 0.48
Log likelihood = -1228.7066

Number of obs = 444

Prob > chi2 = 0.4870

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_fb_friendsplus1	1.016376	.0238731	0.69	0.489	.9706468	1.064261

Table 19.
Cox regression for *Facebook_Shares*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761

Log likelihood = -1178.6633

Number of obs = 444

LR chi2(1) = 100.57
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_fb_sharesplus1	1.424152	.052056	9.67	0.000	1.325693	1.529923

Table 20.
Cox regression for *Comments*

No. of subjects = 444
No. of failures = 221
Time at risk = 12761

Log likelihood = -1198.6752

Number of obs = 444

LR chi2(1) = 60.55
Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_comments_plus1	1.452297	.0623781	8.69	0.000	1.335042	1.579849

Table 21.

Log-rank test for equality of survivor functions for *Video*

chi2(1) = 3.46
Pr>chi2 = 0.0631

Video	Events observed	Events expected
0	9	16.08
1	212	204.92
Total	**221**	**221.00**

Table 22.
Log-rank test for equality of survivor functions for *Pictures*

chi2(1) = 3.15
Pr>chi2 = 0.0757

Pictures	Events observed	Events expected
0	49	60.61
1	172	160.39
Total	**221**	**221.00**

Table 23.
Log-rank test for equality of survivor functions for *Media_Coverage*

chi2(1) = 10.30
Pr>chi2 = 0.0013

Mediacoverage	Events observed	Events expected
0	185	199.06
1	36	21.94
Total	**221**	**221.00**

Table 24.
Cox Regression Model with baseline variables and *Facebook_Friends*

No. of subjects = 441 Number of obs = 441
No. of failures = 221
Time at risk = 12660
LR chi2(11) = 187.78
Log likelihood = -1133.177 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.9017722	.0108188	-8.62	0.000	.880815	.923228
1.group_dummy	1.528307	.4351028	1.49	0.136	.8747361	2.670203
1.group_mixed	1.318882	.3595745	1.02	0.310	.772926	2.250474
1.video	2.019865	.7071708	2.01	0.045	1.016974	4.011758
1.pictures	1.489565	.2609665	2.27	0.023	1.056652	2.099843
percsucc_projects_created	1.568313	.3921243	1.80	0.072	.9607434	2.560107
lnmoneygoal	.6666694	.0386304	-7.00	0.000	.5950965	.7468505
1.facebook	.7653553	.2604671	-0.79	0.432	.3928083	1.491233
projects_created	1.006423	.012471	0.52	0.605	.9822744	1.031165
projects_backed	1.030051	.0059236	5.15	0.000	1.018506	1.041727
ln_fb_friendsplus1	1.063422	.0557307	1.17	0.241	.9596145	1.178459

Table 25.
Stepwise Cox Regression Model with baseline variables and *Facebook_Friends*

No. of subjects = 441 Number of obs = 441
No. of failures = 221
Time at risk = 12660
LR chi2(7) = 184.95
Log likelihood = -1134.5886 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.9010472	.0106684	-8.80	0.000	.8803782	.9222014
projects_backed	1.029371	.0056264	5.30	0.000	1.018403	1.040458
lnmoneygoal	.674188	.0384468	-6.91	0.000	.6028922	.7539149
group_dummy	1.925773	.2942505	4.29	0.000	1.427397	2.598156
pictures	1.508687	.2600534	2.39	0.017	1.07616	2.115053
percsucc_projects_created	1.716339	.4051056	2.29	0.022	1.080674	2.725908
video	2.037418	.710036	2.04	0.041	1.029054	4.033872

Table 26.
Cox Regression Model with all variables, including the virality variables

No. of subjects = 441 Number of obs = 441
No. of failures = 221
Time at risk = 12660
LR chi2(14) = 441.82
Log likelihood = -1006.1536 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8723735	.0112626	-10.58	0.000	.8505761	.8947295
lnmoneygoal	.3760144	.0303321	-12.13	0.000	.321026	.4404216
1.group_dummy	1.139451	.331439	0.45	0.654	.6443202	2.015069
1.group_mixed	1.165472	.3181436	0.56	0.575	.6825679	1.990021
1.video	1.555418	.5516917	1.25	0.213	.7761298	3.117167
1.pictures	1.026338	.1936793	0.14	0.890	.709024	1.485662
percsucc_projects_created	.9195619	.2362496	-0.33	0.744	.5557689	1.521485
projects_created	1.005607	.0120112	0.47	0.640	.9823387	1.029426
projects_backed	1.019069	.0064165	3.00	0.003	1.00657	1.031723
1.facebook	1.850117	.6646224	1.71	0.087	.9149974	3.740921
ln_fb_friendsplus1	.9172445	.0499347	-1.59	0.113	.8244148	1.020527
ln_fb_sharesplus1	2.105953	.1418128	11.06	0.000	1.845566	2.403077
ln_comments_plus1	1.492872	.1048807	5.70	0.000	1.300834	1.713259
1.mediacoverage	1.07129	.224268	0.33	0.742	.7107441	1.614734

Supplementary analysis.

Multicollinearity check

Looking at the relationships between the explanatory variables and each project category, we can verify whether each explanatory variable has different relationship with speed of funding depending on the considered project category. We run the Cox regression model; however, we notice that we have a collinearity problem, that is not easy to identify. In order to solve this problem and understand where the collinearity comes from, we run the simplified model in which we consider, apart from the categories (Dummy variables), the interactions among the project categories and each explanatory variable, one at a time. In this way, we understand the collinearity problems sits.

Campaign Length

Starting with the *Campaign Length* variable, we run the model and we can say that we do not have any collinearity problem.

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(31) = 227.63
Log likelihood = -1115.1339 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.9128141	.0314103	-2.65	0.008	.8532811	.9765007
projects_backed	1.034412	.0066756	5.24	0.000	1.021411	1.047579
lnmoneygoal	.7047658	.0428153	-5.76	0.000	.6256527	.7938826
group_dummy	2.076801	.3577565	4.24	0.000	1.481714	2.910889
pictures	1.594565	.2922986	2.55	0.011	1.113292	2.283891
percsucc_projects_created	1.715328	.4265747	2.17	0.030	1.053579	2.79272
video	1.874169	.6677101	1.76	0.078	.9322903	3.767613
fashion	.0550952	.1089452	-1.47	0.143	.0011427	2.656306

art	1.38607	1.891704	0.24	0.811	.0955143	20.11417
comics	.0126235	.0224389	-2.46	0.014	.0003874	.4113692
dance	6.883877	22.53912	0.59	0.556	.0112418	4215.303
design	2.021393	3.436372	0.41	0.679	.0722115	56.58417
film_video	.6774277	.8471136	-0.31	0.755	.0584047	7.857389
publishing	1.946655	2.663113	0.49	0.626	.1332927	28.42966
food	.5747403	1.022452	-0.31	0.756	.0175873	18.78205
games	.589967	.9747029	-0.32	0.749	.0231489	15.03572
music	1.042141	1.238652	0.03	0.972	.1014421	10.70618
photography	10.97731	57.61057	0.46	0.648	.0003743	321907.2
technology	6.065213	17.1035	0.64	0.523	.0241276	1524.678
fash_campaign	1.022046	.0565923	0.39	0.694	.9169336	1.139207
art_campaign	.9794584	.0407728	-0.50	0.618	.9027183	1.062722
comics_campaign	1.113391	.0574034	2.08	0.037	1.00638	1.23178
dance_campaign	.9271992	.0970854	-0.72	0.470	.7551709	1.138416
design_campaign	.9614208	.0484732	-0.78	0.435	.8709584	1.061279
food_campaign	.984439	.0542936	-0.28	0.776	.8835752	1.096817
film_campaign	.9836617	.0368283	-0.44	0.660	.9140644	1.058558
games_campaign	.9741352	.0478162	-0.53	0.593	.8847841	1.07251
music_campaign	.9835432	.0349676	-0.47	0.641	.9173414	1.054523
photography_campaign	.8985045	.1488052	-0.65	0.518	.649455	1.243058
publishing_campaign	.9593124	.0404445	-0.99	0.324	.8832295	1.041949
technology_campaign	.9135255	.0782132	-1.06	0.291	.7724021	1.080433

Projects_Backed

Proceeding with the *Projects_Backed* variable, we run the model and we can say that we do not have any collinearity problem.

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(30) = 236.60
Log likelihood = -1110.6476 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8978877	.0109825	-8.81	0.000	.8766183	.9196731
projects_backed	1.092547	.1045936	0.92	0.355	.9056316	1.318041
lnmoneygoal	.7003342	.0431434	-5.78	0.000	.6206802	.7902105
group_dummy	1.95388	.3326789	3.93	0.000	1.399482	2.7279
pictures	1.603817	.2940064	2.58	0.010	1.119736	2.297176
percsucc_projects_created	1.424415	.405734	1.24	0.214	.8150386	2.489402
video	2.051019	.7302853	2.02	0.044	1.020683	4.121433
fashion	.1983527	.1426851	-2.25	0.025	.0484313	.812363
art	.9695789	.5450626	-0.05	0.956	.3221573	2.918087
comics	.3192452	.214759	-1.70	0.090	.085411	1.19326
dance	.6829435	.4529352	-0.57	0.565	.1861483	2.505593
design	.8385518	.5033972	-0.29	0.769	.2585466	2.7197
film_video	.5299496	.2682584	-1.25	0.210	.1964987	1.429254
publishing	.6260872	.3285592	-0.89	0.372	.223841	1.751177
food	.3689895	.2212848	-1.66	0.096	.1139054	1.195318
games	.2981452	.1701895	-2.12	0.034	.0973954	.912677
music	.6849278	.3479754	-0.74	0.456	.2530431	1.853937
photography	8.06e-60	.	.	.	.	.
technology	.2021961	.1810969	-1.78	0.074	.0349457	1.169907
fash_backed	.5277929	.3961893	-0.85	0.395	.1212011	2.298373
art_backed	.9061222	.1035553	-0.86	0.388	.7242826	1.133615
comics_backed	.9891606	.0977391	-0.11	0.912	.8150035	1.200533
dance_backed	1.065858	.1836107	0.37	0.711	.7604431	1.493937
design_backed	.8890221	.1056209	-0.99	0.322	.7043442	1.122122
food_backed	.9645652	.0951733	-0.37	0.715	.7949573	1.17036
film_backed	.9281557	.0909388	-0.76	0.447	.7659878	1.124656
games_backed	.9478856	.0909406	-0.56	0.577	.7854007	1.143986
music_backed	.9928431	.1031057	-0.07	0.945	.8099986	1.216962

photography_backed	3.86e+08	6.31e+07	120.88	0.000	2.80e+08	5.32e+08
publishing_backed	.9473693	.0933155	-0.55	0.583	.7810454	1.149112
technology_backed	1.091708	.1537405	0.62	0.533	.8283909	1.438724

Money_Goal

The next step is to analyze the variable Money Goal and see that the collinearity problem does not exist.

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(30) = 233.23
Log likelihood = -1112.3329 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.89648	.0110028	-8.90	0.000	.8751722	.9183065
projects_backed	1.036687	.0064024	5.83	0.000	1.024214	1.049312
lnmoneygoal	.5120816	.2039134	-1.68	0.093	.2346317	1.117614
group_dummy	2.037437	.3506601	4.14	0.000	1.45407	2.854849
pictures	1.554698	.2868235	2.39	0.017	1.082953	2.231941
percsucc_projects_created	1.701951	.4199535	2.16	0.031	1.049336	2.760448
video	2.079189	.7426729	2.05	0.040	1.032405	4.187334
fashion	.0002066	.0012229	-1.43	0.152	1.89e-09	22.60909
art	.0244307	.0885838	-1.02	0.306	.00002	29.8078
comics	.0759633	.3197606	-0.61	0.540	.0000198	290.8431
dance	79.9071	386.583	0.91	0.365	.0060891	1048619
design	.0361241	.1330584	-0.90	0.367	.0000265	49.32752
film_video	.0481281	.168023	-0.87	0.385	.0000514	45.08991
publishing	.0114129	.0422054	-1.21	0.226	8.12e-06	16.03915
food	.0020718	.0090564	-1.41	0.157	3.94e-07	10.89235
games	.0115849	.0453739	-1.14	0.255	5.37e-06	24.98845
music	.0341787	.1209905	-0.95	0.340	.0000332	35.23382

photography	3.03e+26	.	.	.	.	.
technology	.0184646	.0761418	-0.97	0.333	5.71e-06	59.75924
fash_goal	2.046346	1.339743	1.09	0.274	.5671497	7.383472
art_goal	1.492493	.6361211	0.94	0.347	.6473191	3.44117
comics_goal	1.226147	.6016767	0.42	0.678	.4686556	3.207979
dance_goal	.5582138	.3243657	-1.00	0.316	.1787254	1.743472
design_goal	1.377059	.5899255	0.75	0.455	.5947052	3.188623
food_goal	1.79245	.8896479	1.18	0.240	.6775944	4.741595
film_goal	1.279622	.5223187	0.60	0.546	.5749585	2.847914
games_goal	1.423818	.6452965	0.78	0.436	.5857021	3.461245
music_goal	1.40267	.5825905	0.81	0.415	.6214615	3.165898
photography_goal	.0002468	.0000428	-47.85	0.000	.0001756	.0003468
publishing_goal	1.565366	.6747456	1.04	0.299	.6725252	3.643539
technology_goal	1.383655	.6537976	0.69	0.492	.548053	3.493279

Group

For the *Group* variable, we notice that we have a collinearity problem, so we remove the interactions that are omitted in the model: *Dance_Group, Photography_Group, and Technology_Group.*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(28) = 227.45
Log likelihood = -1115.2231 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8995387	.0109125	-8.73	0.000	.8784029	.921183
projects_backed	1.038865	.0060309	6.57	0.000	1.027111	1.050752
lnmoneygoal	.6780166	.0419963	-6.27	0.000	.6005055	.7655326
group_dummy	1.218412	1.235799	0.19	0.846	.1668959	8.894928
pictures	1.63977	.2993831	2.71	0.007	1.146499	2.345266

percsucc_projects_created	1.765365	.4309393	2.33	0.020	1.094081	2.848521
video	2.011122	.7203791	1.95	0.051	.9966436	4.058231
fashion	.0831657	.1220306	-1.69	0.090	.0046877	1.475465
art	.3079359	.3465342	-1.05	0.295	.0339285	2.794835
comics	.3129367	.3685747	-0.99	0.324	.0311112	3.147718
dance	.6442605	.330703	-0.86	0.392	.2355778	1.76193
design	.2308745	.2706854	-1.25	0.211	.0231952	2.298024
film_video	.431743	.4802108	-0.76	0.450	.0488053	3.819297
publishing	.2894226	.3158815	-1.14	0.256	.0340812	2.457821
food	.4750235	.697947	-0.51	0.612	.0266719	8.460118
games	.0573519	.0747794	-2.19	0.028	.0044534	.7385889
music	.3562775	.3878331	-0.95	0.343	.0421887	3.008715
photography	.2006219	.2962725	-1.09	0.277	.0111007	3.62583
technology	.2392684	.1884053	-1.82	0.069	.0511246	1.1198
fash_group	1.360699	2.097594	0.20	0.842	.0663111	27.92142
art_group	2.819792	3.144747	0.93	0.353	.3169002	25.09064
comics_group	1.207515	1.437095	0.16	0.874	.1171804	12.44313
dance_group	1	(omitted)				
design_group	2.863889	3.347403	0.90	0.368	.2897644	28.30526
food_group	.6894812	1.010914	-0.25	0.800	.0389489	12.20533
film_group	.8169453	.8802703	-0.19	0.851	.0988578	6.751105
games_group	5.050092	6.441757	1.27	0.204	.4145054	61.52737
music_group	1.725245	1.81718	0.52	0.605	.2189224	13.59601
photography_group	1	(omitted)				
publishing_group	2.05324	2.205789	0.67	0.503	.2500329	16.86097
technology_group	1	(omitted)				

Pictures

Since we notice a collinearity problem for some variables, we remove them: *Comics_Pictures, Design_Pictures, and Photography_Pictures.*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(24) = 232.43
Log likelihood = -1112.733 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8974618	.0107982	-8.99	0.000	.8765453	.9188773
projects_backed	1.036326	.006176	5.99	0.000	1.024291	1.048501
lnmoneygoal	.6996354	.0418539	-5.97	0.000	.6222298	.7866704
group_dummy	2.08944	.3482401	4.42	0.000	1.507173	2.896656
pictures	1.205122	.9943043	0.23	0.821	.239185	6.071946
percsucc_projects_created	1.621955	.3922076	2.00	0.045	1.009737	2.605369
video	1.930295	.7000036	1.81	0.070	.9482949	3.929199
fashion	7.00e-10	4.41e-10	-33.41	0.000	2.03e-10	2.41e-09
art	.5301412	.537807	-0.63	0.532	.0725908	3.871697
comics	.4764773	.2348033	-1.50	0.132	.1813755	1.251716
dance	.835342	.7851124	-0.19	0.848	.1323872	5.270874
design	.6089326	.2863533	-1.05	0.291	.2422634	1.530561
film_video	.4901246	.38079	-0.92	0.359	.1069022	2.24712
publishing	.2866218	.2315438	-1.55	0.122	.0588406	1.39618
food	1.33e-09	6.49e-10	-41.91	0.000	5.12e-10	3.46e-09
games	1.68e-09	8.11e-10	-41.91	0.000	6.54e-10	4.33e-09
music	.5653591	.4345515	-0.74	0.458	.1253332	2.55025
photography	.3706669	.4047018	-0.91	0.363	.0436138	3.150237
technology	1.67e-09	1.06e-09	-31.88	0.000	4.82e-10	5.79e-09
fash_pictures	2.01e+08	.	.	.	.	.
art_pictures	1.479057	1.636783	0.35	0.724	.1690486	12.94071
comics_pictures	1	(omitted)				

dance_pictures	.6596611	.7422772	-0.37	0.712	.0726967	5.985868
design_pictures	1	(omitted)				
food_pictures	3.14e+08	.	.	.	.	.
film_pictures	.7545432	.6693042	-0.32	0.751	.1326297	4.292668
games_pictures	1.73e+08	.	.	.	.	.
music_pictures	1.1299	.9845441	0.14	0.889	.2048052	6.233599
photography_pictures	1	(omitted)				
publishing_pictures	2.566574	2.337222	1.04	0.301	.4307416	15.29294
technology_pictures	2.18e+08	.	.	.	.	.

Percentage of previous projects created

Since there is multicollinearity, we remove the variable *Technology_Percentageofprojectscreated.*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(28) = 228.78
Log likelihood = -1114.556 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
campaign_length	.8972464	.0110379	-8.81	0.000	.8758713	.9191432
projects_backed	1.036914	.0064087	5.87	0.000	1.024429	1.049552
lnmoneygoal	.6895046	.0420127	-6.10	0.000	.611888	.7769666
group_dummy	2.045954	.3519358	4.16	0.000	1.460414	2.866261
pictures	1.602572	.2909662	2.60	0.009	1.12272	2.287512
percsucc_projects_created	6.802466	7.927466	1.65	0.100	.6929345	66.77911
video	2.031191	.7194212	2.00	0.045	1.014533	4.066635
fashion	.1264288	.0764243	-3.42	0.001	.0386641	.4134133
art	.6864957	.2887902	-0.89	0.371	.3009957	1.565724
comics	.3698312	.1899028	-1.94	0.053	.1351837	1.011773
dance	.6708511	.3760179	-0.71	0.476	.2236249	2.012482

design	.5199026	.2315622	-1.47	0.142	.2171705	1.244638
film_video	.4183363	.1562905	-2.33	0.020	.2011483	.8700308
publishing	.518255	.2078776	-1.64	0.101	.2361117	1.137547
food	.3742027	.17388	-2.12	0.034	.1505154	.9303212
games	.2768271	.1243119	-2.86	0.004	.114807	.6674963
music	.6327482	.2368884	-1.22	0.222	.3037791	1.317965
photography	.535786	.5752182	-0.58	0.561	.0653347	4.393784
technology	.2435608	.1648155	-2.09	0.037	.0646557	.9175042
fash_percsucc	3.46e-20	.	.	.	.	.
art_percsucc	.6265665	.9722258	-0.30	0.763	.0299351	13.11454
comics_percsucc	.4269605	.5646757	-0.64	0.520	.0319619	5.703514
dance_percsucc	.2297696	.3298849	-1.02	0.306	.0137786	3.831597
design_percsucc	5.347006	8.473737	1.06	0.290	.2394186	119.4162
food_percsucc	.0644465	.1841736	-0.96	0.337	.000238	17.44788
film_percsucc	.1842447	.2340907	-1.33	0.183	.0152724	2.22271
games_percsucc	.0631257	.1169984	-1.49	0.136	.0016694	2.386933
music_percsucc	.1951811	.2451377	-1.30	0.193	.0166483	2.288255
photography_percsucc	2.06e-20	.	.	.	.	.
publishing_percsucc	.2994838	.3869422	-0.93	0.351	.023801	3.768354
technology_percsucc	1	(omitted)				

Video

Since there is multicollinearity for some variables, we remove *Comics_Video, Design_Video, Technology_Video, and Photography_Video.*

No. of subjects = 444 Number of obs = 444
No. of failures = 221
Time at risk = 12761
LR chi2(25) = 228.22
Log likelihood = -1114.8378 Prob > chi2 = 0.0000

_t	Haz. Ratio	Std. Err.	z	P>z	[95% Conf.	Interval]
campaign_length	.8974061	.0108647	-8.94	0.000	.8763623	.9189552
projects_backed	1.03542	.0063207	5.70	0.000	1.023105	1.047883
lnmoneygoal	.698268	.0421042	-5.96	0.000	.6204351	.785865
group_dummy	2.13076	.3628373	4.44	0.000	1.526116	2.974964
pictures	1.578143	.2910667	2.47	0.013	1.099396	2.265368
percsucc_projects_created	1.710269	.4152124	2.21	0.027	1.062706	2.752427
video	1.387187	1.497331	0.30	0.762	.1672426	11.50596
fashion	4.49e-10	2.77e-10	-34.97	0.000	1.35e-10	1.50e-09
art	.4096683	.5877098	-0.62	0.534	.0246207	6.816559
comics	.4638055	.2203637	-1.62	0.106	.1827731	1.176954
dance	2.752104	3.933396	0.71	0.479	.1671475	45.31371
design	.5969119	.2696636	-1.14	0.253	.2462451	1.446948
film_video	.3283481	.4114743	-0.89	0.374	.0281604	3.828514
publishing	.2100171	.3019876	-1.09	0.278	.01254	3.517332
food	11.78737	17.10602	1.70	0.089	.6857097	202.6254
games	8.11e-09	3.72e-09	-40.61	0.000	3.30e-09	1.99e-08
music	.3401277	.4213964	-0.87	0.384	.0299956	3.856791
photography	.361533	.3921527	-0.94	0.348	.0431375	3.02999
technology	.3199912	.1984142	-1.84	0.066	.0949163	1.078786
fash_video	2.99e+08	.	.	.	.	.

art_video	1.88913	2.813253	0.43	0.669	.1020164	34.98272
comics_video	1	(omitted)				
dance_video	.2148506	.3283997	-1.01	0.314	.0107417	4.297348
design_video	1	(omitted)				
food_video	.0282104	.0430898	-2.34	0.019	.0014133	.563081
film_video2	1.286735	1.689445	0.19	0.848	.0981492	16.86908
games_video	3.28e+07	.	.	.	.	.
music_video	1.939428	2.514027	0.51	0.609	.1528567	24.60723
photography_video	1	(omitted)				
publishing_video	2.77334	4.121633	0.69	0.492	.1506536	51.05365
technology_video	1	(omitted)				

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