Industry specificity and the effect of internal social capital in reward-based crowdfunding

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Abstract: Literature on crowdfunding has highlighted the role of social capital developed within the platform (internal social capital) in determining the success of a funding campaign. However, to date, prior studies have neglected that industry specificity may influence this effect. In this paper, we aim at filling this gap by investigating how social capital influence the funding of products belonging to different industries. Using a dataset of 34,121 project launched on Kickstarter during 2014, we found that internal social capital effect varies by industries and is stronger in magnitude when the industry is characterized by high demand uncertainty and task complexity. Overall, these findings contribute to a better understanding of the role of social capital in early stage financing.

Key words: Crowdfunding, Social Capital, Industry Specificities

Introduction

A beautiful, lush, floating pool on the banks of the Thames[1]. A film containing Orson Wells' last memories[2]. A space defense system to prevent asteroid smashes[3]. All these entrepreneurial projects share some common ground: They sought for money through reward-based crowdfunding campaigns.

Reward-based crowdfunding, the practice of collecting monetary contribution from the crowd in exchange for the delivery of products or services (Belleflemme et al., 2014), is gaining more and more resonance worldwide (The Guardian, 2014). The growth of the phenomenon has been extraordinary. In less than five years, more than 400.000 projects have been crowdfunded and more than $5 billion have been collected through crowdfunding platforms (Crowdfunding Industry Report, 2015). This increasing economic relevance leaded researchers from different fields, such as economics (Acemoglu et al., 2014), management (Mollick, 2014) and information technology (Walsh, 2014), to start studying this phenomenon.

Initial contributions have mainly focused on discriminating reward-based crowdfunding from somewhat similar phenomena, such as peer-to-peer lending (Zhang and Liu, 2012), micro-credit (Khandker, 1998) and equity crowdfunding (Agrawal et al., 2013). Concurrently, scholars have stressed that the advantages of reward-based crowdfunding go beyond the collection of capital, and relate also to collecting non-financial resources in the form of feedbacks (Agrawal et al., 2013; Colombo et al. 2015a) and social capital (Butticè et al., 2016). In this vein, reward-based crowdfunding is seen promoting the development of new entrepreneurial ecosystems (Lambert and Schwienbacher, 2010; Frydrych et al., 2014) and favoring the diffusion of startups (Weber and Hine, 2015). This is particularly true for those individual located in places not known for entrepreneurship, who are often excluded from traditional forms of entrepreneurial funding (Fleming and Sorenson, 2016). Crowdfunding is reported to be a way to democratize access to the capital and helps startups located out of traditionally venture capital hubs to emerge (Mollick and Robb, 2016). Crowdfunding also arose as a valuable source of funding for highly risky startups (Agrawal et al., 2016) and women

[1] https://www.kickstarter.com/projects/thamesbaths/thames-baths-a-new-beautiful-lido-for-the-river-th
[2] https://www.indiegogo.com/projects/finish-orson-welles-last-film
[3] https://www.indiegogo.com/projects/help-defend-earth-against-asteroid-threats#/story

(Mollick and Robb, 2016) which are often excluded from VC funding. Given these results, it seems reasonable to believe that crowdfunding may allow a more diverse spectrum of people to become entrepreneurs, and, in turn, may lead to the transformation of the entrepreneurial ecosystem (Zacharakis et al., 2003; Mathews, 1997).

Given these premises, focusing on understanding how entrepreneurs can take advantage of crowdfunding is an immediate consequence. Several recent studies have examined factors that drive entrepreneurs to succeed in collecting funding through a reward-based crowdfunding campaign. Scholars have highlighted the role of the design of the campaign (Belleflemme et al., 2014), proponent's human capital (Ahlers et al., 2014), and backers' commitment (Kuppuswamy and Bayus, 2014WP). Within this strand of literature, project proponent's social capital has been identified as a primary determinant of the success of the campaign. Previous works have stressed the importance of family and friends (Agrawal, et al. 2011) and personal acquaintances (Mollick, 2014), showing that both direct and online contacts are relevant for collecting money. Similarly, Colombo et al. (2015b) consider separately social capital within the crowdfunding platform –i.e. internal social capital– and document that its effect on the success of a reward-based crowdfunding campaign is even greater in magnitude compared to other forms of social capital. However, the authors themselves underline the need for additional research that aim at verifying whether their results hold after controlling for industry specificities. The present paper aims at filling this gap.

In particular, the paper contributes to the current debate on the role of social capital in crowdfunding and more generally in early stage financing (Shane and Cable, 2002; Shane and Stuart, 2002; Zhang & Liu, 2012; Jonsson and Lindebergh, 2013) by analyzing how internal social capital helps to attract financial contributions depending on product characteristics. Similar to Colombo and colleagues (2015b), we maintain that social capital triggers reciprocation through a feeling of mutual obligation (Coleman, 1990). However, we posit that industry specificities influence the effectiveness of this mechanism. Descriptive evidence, indeed, suggests that project proponents in 8 out of 10 cases finance products coming from the same industry of their own product. Therefore, when the product object of the crowdfunding campaign belongs to an industry characterized by high demand uncertainty and task complexity, it is highly likely that the proponent had financed the same kind of product in the past. In the funding of such products, repeated interactions with the other members of the community are favored. These conditions lead to the emergence of embedded relationships and

make social norms of reciprocity stronger. Therefore, we expect that for these products internal social capital positive effect is greater in magnitude.

To test our hypothesis, we use a set of probit models on a sample of 34121 projects launched during the first nine months of 2014 on Kickstarter. Results fully support our arguments that the effect of the proponent's internal social capital on the probability of project success changes in magnitude depending on the characteristic of the industry. In particular, social capital developed within the platform has a greater effect in industries such as Technology, Fashion Design and Videogames, characterized by high uncertainty. In addition, in line with the results of Colombo et al. (2015b), we show that the effect of internal social capital is greater than that of external social capital, independent from the industry. The paper is organized as follows. The next section presents the conceptual background and research hypotheses. It is followed by a presentation of the data and methodology. We next illustrate the econometric models and empirical results and we discuss the robustness of the estimates. The final section discusses implications for scholars and practitioners.

Theoretical background

Several studies have highlighted that project proponents' social capital, namely the sum of actual and potential resources embedded within the networks of connections (Nahapiet and Ghoshal, 1998) and available to project proponents through the contacts these networks bring (Burt, 2000), plays a prominent role in the attraction of financial resources during a crowdfunding campaign.

Agrawal et al. (2011), by investigating the role of geography in influencing the dynamics of success of a crowdfunding project, showed that the majority of the early backers are people with whom the proponents have social contacts including close friendship and familiar relationships. These contacts play a key role in determining the overall success of the campaign by providing an indirect clue about project quality and triggering imitating behavior. A similar result is highlighted by Ordanini and colleagues (2011) who stressed that in the initial phase of a crowdfunding campaign, contributions are primarily made by close friends of the proponents.

Literature have highlighted that also online social connections have a positive effect on the success of the crowdfunding campaign. Mollick (2014) shows that the number of Facebook friends of proponents is positively related to the number of backers. Moreover, he finds that not

having a Facebook account is better than having few Facebook friends. In a similar vein, Colombo and colleagues (2015b) highlight that also professional acquaintances, proxied by the number of LinkedIn connections, are positively related with early backers. In general, these studies confirm the findings of prior literature on early stage financing which stressed that social capital helps overcoming the information asymmetries between emerging entrepreneurs and external investor (Shane and Cable, 2002; Jonsson and Lindbergh, 2013).

Colombo and colleagues (2015), make a further step in examining the role of social capital for the success of a crowdfunding campaign. The authors document that social capital developed within the platform (i.e. internal social capital) has a positive effect on the probability of collecting funding and its effect is even greater in magnitude compared with other form of social capital. According to the authors, financing other's projects leads to embedded relationships within the platform and engenders the raise of unwritten social norms of reciprocity. Therefore, in such a setting, proponents who had developed several social ties are more likely to receive monetary contributions. In this paper, we move from these argument and acknowledge that the emergence of norms of reciprocity not only depends on the number of project that the proponents had backed in the past but it is also affected by the industry the product belongs.

Prior research, indeed, has suggested that product specificities influence the proportion of embedded ties in a network (Jonsson and Lindebergh, 2013). Specifically, products belonging to industries characterized by higher levels of demand uncertainty and tasks complexity lead to repeated interactions between project proponents and backers (Jones et al., 1997). Bakers, especially in the early phases of the crowdfunding campaign offer suggestions and feedbacks that proponents use to improve their products and make them more suitable to customers tastes (Colombo et al., 2015).These repeated interactions engender greater social identification with the proponent (Moran, 2005). Thus, such products help the proponent to develop embedded relationships within platform (Granovetter, 1992) and ultimately strengthen the norms of reciprocity across the community (Coleman, 1990; Williamson, 1985).

Demand uncertainty is generated by rapid shifts in consumer preferences and seasonality. These conditions are well exemplified in both the entertainment industry (e.g. Music), wherein it is difficult to ascertain what makes a new album a hit (Peterson and Berger, 1971) and the haute cousine industry, where customers are always looking for novel and tasteful dishes (Rao et al., 2003; Petruzzelli and Savino, 2014). Another case in point is the fashion industry (Uzzi, 1997),

where heterogeneous demand (Djelic and Ainamo, 1999), short life cycles (Fisher et al., 1994) and tremendous variety (Sen, 2008) make predicting demand a difficult task.

Task complexity, which refers to the number of different specialized inputs needed to complete a product or service (Pfeffer and Salancik, 1978), leads to repeated exchanges between the members of the community and the proponent. Industries that exhibit this feature are, with no doubt, the high-tech industry (Barley et al., 1992), and the videogames industry (Tschang, 2007).

Therefore, we expect:

> H1: *The magnitude of the effect of social capital on the probability of success in a crowdfunding campaign varies across industries.*
>
> H2: *The effect of social capital is higher in industry characterized by higher level of demand uncertainty and task complexity. Such industries comprehend Music, Haute Cousine, Fashion Design, High-Tech and Games.*

Sample and variable

To test the hypotheses presented in this paper, we collected all the projects posted on Kickstarter from January 1, 2014 to September 12, 2014. Focusing on Kickstarter offers several advantages. First, the platform is the largest existing crowdfunding platform both in terms of money collected and projects financed (Colombo et al., 2015b). From its inceptions, about 232,000 projects have been lunched in the platform so far, and of these about 85,000 have been successfully funded collecting more than 1.73 billion $[4]. Therefore, Kickstarter provides numerous and easily accessible data for examining the effects of social capital on the success of a campaign. Second, Kickstarter has a generalist target and host crowdfunding campaigns in a large number of categories, including art, dance and theater, fashion design, film, food, games, music, publishing and technology. This allows us to investigate the effects of both internal and external social capital on projects belonging to different industries. Third, this setting offers an ideal test-bed for empirical work. Indeed, it allows us to control for virtually each and all the information that backers could use at the time they took the decision on whether or not to fund the project. Finally, Kickstarter.com data have been used in several prior studies of

[4] https://www.kickstarter.com/help/stats?ref=footer Accessed on March 17, 2016

crowdfunding (Mollick, 2013; Kuppuswamy and Bayus, 2013; Colombo et al., 2015), making results comparable and potentially replicable.

Our unit of analysis is the crowdfunding campaign. For each of these, we collected three sets of information. First, we collected information related to the project: the number of visuals (videos plus images) contained within the project description (*ln_visuals*), the industry, the duration of the campaign (*duration*), the number of links to external websites with further information about the project (*more_information*), and the target capital of the campaign expressed in dollars (*ln_target*). When the project was expressed in currencies different from dollar, we used a monthly avarege exchange rate to make all the figures comparable.

A second set of information related to the rewards offered in the campaign. Kickstarter, indeed, allows the proponents to offer a wide variety of rewards besides the product presale. Several projects offer customized products, such as a videogames special edition with the main character who shares the backer's traits. Similarly, projects offer what we call "*ego-boosting*" types of rewards, such as including the backer's name in a public in the film credits, and projects offering "*community-belonging*" types of rewards are widely diffused. The latter type of reward involves events that provide opportunities for social interaction (e.g., an invitation to a development workshop or to a launch party) and the offering of symbolic objects (e.g., a branded outfit) meant to display support for a project. We created a set of dummy variables indicating the presence of customized reward (*d_customized*), ego boosting rewards (*d_ego*) and community rewards (*d_community*). In order to create rewards variables we run a content analysis algorithm, based on a search of characterizing terms in the textual description of the rewards[5]. We tested the appropriateness of this methodology by running the algorithm on a test-sample of 669 projects whose rewards had been human-classified. Evaluations obtained through the algorithm were in line with the results provided by the evaluators[6].

Finally, a third set of information relates to proponents. We coded internal social capital as represented by the number of Kickstarter projects that the proponent had financed at the time of the launch of the focal project (*int_social_capital*). This represents the degree to which a proponent had been active within the platform and is a proxy of the social connections with peers she had established in the community (Colombo et al., 2015). Moreover, we recorded

[5] Thus, in building, for instance, the variable *d_customized* we looked at the presences of textual descriptions containing the root "*custom"* or its synonyms. The full dictionary is available upon request to the corresponding author.

[6] The results of the algorithm were concordant with those provided by the evaluators in the 98% of the cases.

information about the number of proponent's facebook friends. This information is intended as a proxy of external social capital (ext_social_capital) and is available on the Kickstarter platform. We tend to prefer this measure of external social capital for two reasons. First, the same variable has been widely used in prior studies (e.g. Mollick, 2014; Kuppuswamy and Bayus; 2015), making our results easily comparable with extant literature. Second, the number of Facebook friends, unlike LinkedIn connections, comprises also the relationships based on kinship and friendship. These relationships play a significant role in influencing the funding dynamics (Agrawal et al., 2011) and are especially important when the product has a highly creative content (Caves, 2000), such as many of the product on Kickstarter. Information about Facebook friends had been collected as of the time of project launching. Finally, we coded whether the proponent was located in the United States by mean of a dummy variable (d_USA).

The summary statistics and definitions of the variables are shown in Table 1.

Descriptive Statistics

Table 2 reports preliminary descriptive statistics by industry.

First, we report the number of crowdfunding campaign presented in each industry. We can notice that project belonging to the categories Film, Music, Games and Newsstand represents more than fifty-five percent of the overall campaigns. On the contrary, projects related to theater and dance are rather rare (less than 4% of the total campaigns). Finally, projects in the categories Technology, Food, Fashion and Art represent each around 9% of the population.

Being Kickstarter an "all or nothing platform", which means that the money is cashed in by the proponent only if the capital pledged by the end of the campaign is equal to or greater than the target amount, we created a dummy variable *success* taking value 1 if the capital raised exceed the target capital. Not surprisingly (Mollick, 2014; Colombo et al., 2015), success is not evenly distributed by project categories[7]. Indeed, successful campaigns are more common in categories such as Music, Games and Theater; while their proportion is considerably lower than average in Food and Technology. Descriptive statistics on target capital show a peculiar feature of crowdfunding campaigns. On average, indeed, the total amount of capital that a project seeks to raise is limited (18,451$) with significant variance across projects. As already discussed by

[7] The null hypothesis that successful campaigns are evenly distributed among categories is rejected at conventional confidence levels (Kruskal-Wallis test: $\chi^2[8]=488.87$).

prior literature, crowdfunding is a viable funding method especially addressed to projects with limited financial needs (Schwienbacher and Larralde, 2010). Data in the table confirm this contention. Moreover, figures reported show heterogeneity among categories. Projects belonging to Film, Music and, above all, Technology categories on average tend to ask for more capital. On the contrary, projects related either to artwork or to editorial contents share the tendency to ask for limited monetary amount.

In addition, we computed the ratio between pledged and target capital to create a variable measuring the percentage of capital at closure. The distribution of this variable by industry is reported in Figure 1. The graphs show similarity and differences among categories. Indeed, independent from the typology of project, the distribution of pledged capital follows a bimodal pattern[8]. Some differences exist across categories, referring the first mode. Categories such as Technology and Food have a mode of approximately 0%, while other categories have a mode between 10% and 20% of the target capital. On the contrary, all the categories share the second mode approximately at 100% of the target capital.

Our data show considerably less variation referring to the campaign duration. The typical duration of a funding campaign is 1 month, with 15, 45, and 60 days being other common periods. With limited variance, this result stands by industry.

Results

We test our hypotheses by mean of a set of probit models, wherein the dependent variable is a dummy taking value 1 if the campaign raised at least 100% of the target capital and 0 otherwise. Results are reported in Table 4. The models in Column I and II report the estimates run on the full sample, while the following columns show the estimates by industry.

[Table 4 about here]

Results in model I indicates that all control variables signs are in line with prior crowdfunding literature. As expected, the success of the campaign is negatively related with the duration and the size of the project expressed by the target capital of the campaign (Mollick, 2014). The higher is the capital the project proponent is seeking for, the lower is the probability of success.

[8] The Hartigan dip statistic is always significant at a confidence of 99%.

Likewise, choosing a longer duration of the campaign witnesses a proponent's lack of confidence (Mollick, 2014) and is associated with lower chances of success. The number of images and video (ln_visual) included in the project description shows a positive and significant coefficient. Making a video is strongly suggested by Kickstarter itself and may be regarded as a proxy of project quality (see again Mollick, 2014). Project in the United States are 4.2% more likely to succeed (p-value<0.01). The coefficient of *more_information*, which is a proxy of the completeness of the information provided by the project proponent, is positive and significant (p-value<0.01). With respect to offering only the pre-purchase of the product, offering a customized product within the campaign is associated with a 3.7% increase in the likelihood of success. Likewise offering rewards that foster internal motivations (Deci and Ryan, 1985) entails an increase in the likelihood of success of 4.9% (ego-boosting rewards) and 2.2% (community belonging rewards). All these effects are significant with a confidence of 99%.

Let us now turn attention to the explanatory variables capturing proponents' social capital. As expected, when we run the estimates on the full sample (Column II), both internal and external social capital are positively related with the likelihood of success. This result is in line with prior literature (Colombo et al.,2015; Mollick 2014). Moreover, the magnitudes of the effects of both internal and external social capital is quite relevant. With all continuous covariates at their mean and dummy variables at their median value, a one-standard deviation increase of *int_social_capital* leads to a 48% increase (from 13.4% to 19.6%) in the likelihood of success. Likewise, the corresponding increase of *ext_social_capital*, proxied by the number of facebook friends, entails a 28% (from 13.9% to 17.8%) positive shift in the chances of a project being successful. In line with prior studies, having no Facebook friends is better than having few connections on the famous social network (Mollick, 2014).

Let us consider now consider the estimates relating to the specific industries effect (Models III-XI) In all these models, the effect of internal social capital is positively and significantly related to the probability of success. However, the magnitude of this effect vaires by industry. This supports our hypothesis 1 that the positive effect of social capital developed within the funding platform on the likelihood of success of the campaign varies by industry. To assess the economic magnitude of internal social capital we set all continuous variables at their mean values and all dummy variables at their median value, and we computed the increase in the estimated likelihood of success engendered by a one-standard deviation increase in the independent variable (McDonald & Moffit, 1980). These results are reported in Table 5. The estimates show, in line with hypothesis 2, that the effect of internal social capital is greater in

industry such as Food (33% increase, from 11% to 15%), Games (32% increase, from 34% to 45%), Music (32% increase, from 34% to 45%), and Technology (30% increase, from 12% to 16%). In contrast, the magnitude of the effect of internal social capital is limited for projects belonging to the categories Theater and Dance (7% increase, from 39 to 42%) and Art and Craft (9% increase, from 22 to 24%). Surprisingly, external social capital (ext_soc_capital) has no significant effect in product categories of projects (Food and Games), in which internal social capital has a particularly strong effect. Furthermore, overall, the magnitude of the effect of this variable is weaker than that of internal social capital. Lastly, when we run the estimates on subsamples divided by industry, we lose the positive effect of not having Facebook friends except for the music industry.

Robustness check

Some scholars have advanced caution when comparing how the effects of variables differ across group. Allison (1999), for instance, argues that there is a potential peril in cross-group comparison when doing binary regression models. Indeed, in these models, when residual variation differ across group, it produces an apparent difference in coefficients that may lead to erroneous interpretation. Mood (2010) suggests that comparing marginal effects, as we have done here, is enough for assuring the validity of the interpretation. However, this solution has not been unanimously accepted by scholars because comparing marginal effects actually correspond to estimating a linear probability model in disguise[9]. In this debate heterogeneous choice model (also known as location scale model) have been proposed as a superior mean for dealing with the problem (Williams, 2009). To this end, we run such a model to find confirmation on the validity of our interpretations.

Table 6 shows the results of the model in which the variable "*theater and dance"* has been omitted. Thus, all the results have to be intended as relative effect compared to this baseline. Heterogeneous choice regressions provide two sets of information. First, through the set of parameters *lnsigma,* this category of models provide hints about the residual variation across groups. When *lnsigma* is significantly different from zero, it means that residual variance in the group differs from the one in the baseline. In our estimates, the unexplained variance in all subsamples is significantly lower compared with the category *"theater and dance"*.

[9] See the stata forum for an example: http://www.statalist.org/forums/forum/general-stata-discussion/general/390061-testing-average-marginal-effects-across-samples

Second, as already mentioned, heterogeneous choice models allow us to make a cross group comparison of coefficients. When the interaction terms included in the model are significant, it means that the variable of interest has an either lower or greater effect on the dependent variable compared with the baseline. Therefore, in our case, the magnitude of the effect of *internal social capital* on the success of the campaign is always greater compared with the baseline (*theater and dance)*. In line with the main model the effects of social capital is greater in categories such Music (+3.9%), Food (+3.5%), Fashion (+1.65%) and Technology (+1.12%). Therefore, these estimates further confirm both hypotheses H1 and H2.

Conclusions

Crowdfunding is emerging as powerful way to promote the diffusion of startups (Flemming and Sorenson, 2016) and ultimately to transform existing entrepreneurial ecosystems (Frydrych et al., 2015). Several successful startups has been funded by the crowd over years (Ordanini et al., 2011) and new entrepreneurs residing out of regions where venture capitalists are located have emerged (Mollick and Robb, 2016). Given these results, crowdfunding has generated considerable enthusiasm among scholars (see Butticè et al., 2016 for a comprehensive review), especially regarding the investigation of how entrepreneurs succeed in collecting money from the crowd.

Following prior literature on the topic, in this paper we focus attention on the determinants of success of a crowdfunding campaign. We investigate how the effect of internal social capital (viz. the social capital develop within a community) varies across different industries. We show that the positive effect of internal social on the success of the crowdfunding campaign varies in magnitude depending on the type of product object of the campaign. We posit that industry specificities affect the conditions under which social capital works, namely norms of reciprocity and mutual identification (Nahaphiet and Ghosal, 1998), and consequently influence the effect of social capital in attracting financial contributions. Following extant literature (Jones et al., 1997), we claim that social capital is more relevant in industries characterize by high demand uncertainty and task complexity.

By mean of econometric estimates on a sample of 34121 projects launched on Kickstarter during 2014, we show that internal social capital has a greater effect in magnitude when the crowdfunding campaign relates to a product belonging to industries characterized by high uncertainty and task complexity such as the product categories Music, High-Tech, Games, Food

and Fashion Design. Furthermore, in line with Colombo et al. (2015b) we highlight that social capital developed within the crowdfunding platform always has a greater effect compared with other forms of social capital developed outside the platform. Finally, in contrast with prior studies (Mollick, 2014), we do not find any significant positive effect of not having Facebook friends when we focus on product categories estimates.

The paper contributes to the extant knowledge in a twofold manner. First, it contributes to the nascent crowdfunding literature, showing the importance of industry specificities in influencing the effect of the determinants of success. Specifically, we showed that the effects of both internal and external social capital varies in magnitude by industry. Scholars interested in investigating the crowdfunding phenomenon should carefully consider this heterogeneity when developing their models. Second, the paper contributes to the broader debate on social capital in early stage financing (Shan and Cable, 2002). In so doing, we highlight that the effect of social capital developed within the crowdfunding platform varies by industry and is far from being negligible. We think that our results call for future investigations in order to disentangle the signaling effect of social capital from social obligation and reciprocated behavior.

This paper has some limitations that pave the way for further research. First, in measuring internal social capital as the number of connections within the crowdfunding platform, we do not consider the strength of such ties, disregarding the cognitive dimension of social capital (Foss and Lorenzen, 2009). Studies considering these aspects could enable a more comprehensive understanding of the role of internal social capital in favoring the success of crowdfunding projects. Second, many scholars agree that social capital, by working as a signal of ability and trustworthiness, reduces information asymmetries and, therefore, influences the ability of obtain seed capital (Shane and Stuart, 2002). However, other scholars (e.g. Jonsson and Lindebergh, 2013) show that the links between social capital and seed financing go beyond the reduction of information asymmetries (Spence, 2002) and involve mutual identification and social obligations of reciprocity. In this paper, we are unable to distinguish the effects of these effects or to assess their relative importance. Third, using data from a single platform advances some caution about generalizability of our results. Kickstarter, indeed, hosts projects only from the United States. Therefore, caution should be taken in extending our findings to other countries, because the social norms governing the behavior of members in crowdfunding communities may be culturally mediated. Developing a dataset that includes crowdfunding projects from multiple platforms would allow us to observe whether our results are platform specific rather than generalizable to different context.

Our results have interesting implications for practitioners. Estimates broadly confirm that internal social capital is a critical resource to obtain success in a crowdfunding campaign. However, its effect varies across industry. Platform managers, interested in attracting successful projects, should consider industry specificity when developing functionalities that enables social interactions. Designing functionalities that favor a strong identification and a sense of social proximity among project proponents and backers is a crucial especially for platforms that host project related to music, high-tech, food and fashion design. The study also has interesting implications for proponents whose projects belong to industries characterized by high demand uncertainty and task complexity. For these proponents it becomes crucial backing other members' projects and growing rich social connections within the platform before launching their own campaign.

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Table 1 – Variable description and summary statistics

	Obs.	Mean	St. Dev.	Min.	Max.	Variable description
d_success	34121	0.3103	0.4626	0	1	Dummy=1 if pledged capital is greater or equal to target capital; 0 otherwise.
int_social_capital	34121	3.1703	10.879	0	259	Number of projects that the proponents had backed at the time of campaign launch
ext_social_capital	34121	4.3927	7.1179	0	51.43	Number of facebook connections/100
d_nofacebook	34121	0.3614	0.4804	0	1	Dummy=1 if the proponents has not a Facebook account
duration	34121	33.094	11.135	0	68	Duration of the campaign in days
ln_visuals	34121	1.5676	0.9557	0.6931	5.1239	Ln(Number of pictures and videos in project description+1).
moreinfo	34121	0.8057	0.5716	0	3.3672	Ln(Number of links external to Kickstarter provided in project description+1)
d_US	34121	0.7539	0.4307	0	1	Dummy = 1 if project location is in the United States; 0 otherwise
ln_target	34121	8.4408	1.8523	0.6519	18.871	Ln(Target capital in thousand dollars)
d_ego	34121	0.5615	0.4961	0	1	Dummy = 1 if the project has at least one reward that entails crediting the backers publicly
d_community	34121	0.3897	0.4876	0	1	Dummy = 1 if the project has at least one reward that fosters feelings of community belonging
d_customized	34121	0.2314	0.4217	0	1	Dummy = 1 if the project has at least one reward that offers a customized product or service

Table 2 – Descriptive statistics by project categories

	Technology		Food		News-stand		Fashion and Design		Film	
Number of projects	2772		3308		5827		4418		5289	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Success (%)	0.195	0.396	0.182	0.386	0.2943	0.456	0.294	0.456	0.358	0.479
Target capital ($)	45,323	88,587	20,396	57,297	10,220	31,602	19,082	43,547	23,293	66,525
Capital at closure (%)	1.207	16.90	0.502	3.808	0.683	4.861	1.191	49.45	0.776	13.44
Duration (days)	35.55	11.47	33.40	11.22	33.22	11.02	33.58	10.25	32.23	11.33
	Music		Games		Theater and Dance		Art and Crafts		All	
Number of projects	4666		2813		1627		3401		34121	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Success (%)	0.3585	0.4796	0.382	0.486	0.403	0.491	0.2959	0.456	0.311	0.463
Target capital ($)	23,293	66,525	24,886	68,776	11,653	53,119	10,380	43,280	18,451	55,222
Capital at closure (%)	0.776	13.44	5.277	92.44	1.038	15.77	0.888	8.414	1.794	86.07
Duration (days)	32.23	11.33	32.71	10.30	31.34	11.63	32.07	11.53	33.06	11.10

Table 3 - Correlation Matrix and VIF scores

	1	2	3	4	5	6	7	8	9	10	11	12	VIF
1.success	1												
2.int_social_capital	0.1912*	1											01.08
3.ext_social_capital	0.1123*	0.0605*	1										01.31
4.d_nofacebook	-0.0518*	-0.0598*	-0.4649*	1									01.29
5.duration	-0.1739*	-0.0450*	-0.0135*	0.0046	1								01.06
6.ln_visual	0.2190*	0.2431*	0.0093	-0.0006	-0.0029	1							01.27
7.moreinfo	0.1872*	0.1316*	0.1622*	-0.0974*	-0.0363*	0.2743*	1						01.14
8.d_US	0.0284*	0.0668*	0.0966*	-0.0915*	-0.0069	-0.0276*	0.0211*	1					01.03
9.ln_target	-0.1345*	0.0180*	0.0348*	0.0213*	0.2117*	0.2791*	0.1533*	0.0277*	1				01.16
10.d_ego	0.0972*	0.0188*	0.0459*	-0.0348*	-0.0264*	0.1793*	0.1213*	-0.0111	0.0582*	1			01.10
11.d_community	0.0524*	0.0219*	0.0577*	-0.0385*	0.0066	0.1067*	0.1143*	0.0047	0.0907*	0.2338*	1		01.08
12.d_custom	0.0831*	0.0477*	0.0520*	-0.0434*	-0.0054	0.1764*	0.1236*	0.1104*	0.0872*	0.1503*	0.1225*	1	01.08

***** p-value ≤ 0.05

VIF: variance inflation factor. Mean VIF=1.15

Figure 1- capital at closure

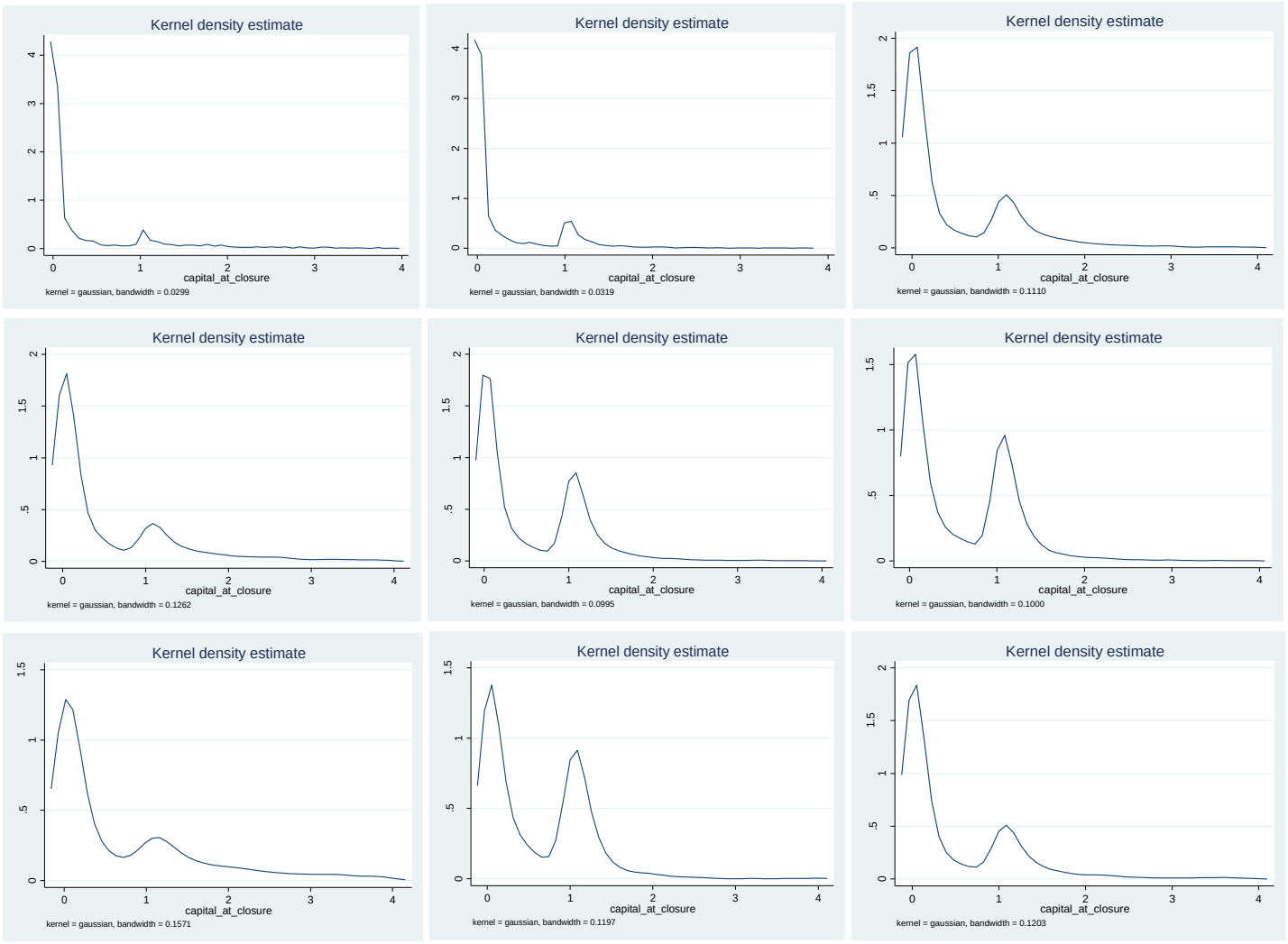

Table 4 - Results

dependent variable: **success**	(I) Controls	(II) Total sample	(III) Technology	(IV) Food	(V) News-stand	(VI) Fashion/Design	(VII) Film	(VIII) Music	(IX) Games	(X) Theater/dance	(XI) Art/Craft
int_social_capital		0.0166***	0.0241***	0.0232***	0.0159***	0.0268***	0.0197***	0.0481***	0.0118***	0.0207***	0.0106***
		(0.001)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.001)	(0.008)	(0.003)
ext_social_capital		0.0195***	0.0229***	0.0017	0.0206***	0.0200***	0.0159***	0.0098***	0.0037	0.0133***	0.0151***
		(0.001)	(0.008)	(0.006)	(0.003)	(0.004)	(0.003)	(0.002)	(0.006)	(0.005)	(0.004)
d_nofacebook		0.0703***	0.0585	-0.0674	0.0380	0.0487	0.0300	0.1739***	0.0327	0.0712	-0.0091
		(0.018)	(0.075)	(0.067)	(0.046)	(0.053)	(0.046)	(0.050)	(0.063)	(0.082)	(0.058)
duration	-0.0194***	-0.0191***	-0.0121***	-0.0208***	-0.0180***	-0.0114***	-0.0209***	-0.0186***	-0.0167***	-0.0201***	-0.0214***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
ln_visual	0.3490***	0.3169***	0.7157***	0.4387***	0.3909***	0.5590***	0.3308***	0.1974***	0.6380***	0.0615	0.3450***
	(0.009)	(0.009)	(0.041)	(0.042)	(0.024)	(0.029)	(0.025)	(0.032)	(0.035)	(0.055)	(0.030)
moreinfo	0.3938***	0.3434***	0.2927***	0.4791***	0.3291***	0.3037***	0.1022***	0.2384***	0.2614***	0.1032	0.3806***
	(0.014)	(0.014)	(0.063)	(0.055)	(0.036)	(0.044)	(0.035)	(0.037)	(0.058)	(0.065)	(0.046)
d_US	0.1251***	0.0684***	0.2635***	0.1827**	0.0027	-0.0495	-0.0033	0.1767***	0.2371***	0.2551***	-0.0570
	(0.018)	(0.018)	(0.072)	(0.080)	(0.045)	(0.051)	(0.044)	(0.052)	(0.063)	(0.079)	(0.056)
ln_target	-0.1782***	-0.1800***	-0.3152***	-0.1081***	-0.2153***	-0.2734***	-0.2527***	-0.1822***	-0.3172***	-0.1783***	-0.1667***
	(0.005)	(0.005)	(0.022)	(0.013)	(0.014)	(0.016)	(0.014)	(0.017)	(0.020)	(0.027)	(0.015)
ego	0.1475***	0.1538***	0.0144	0.0026	0.1276***	-0.0398	0.3588***	0.2027***	-0.0941	0.1373*	0.1304**
	(0.016)	(0.016)	(0.069)	(0.060)	(0.040)	(0.046)	(0.047)	(0.041)	(0.057)	(0.071)	(0.051)
community	0.0661***	0.0587***	-0.0370	0.2541***	0.0404	-0.0621	-0.0316	0.2531***	-0.2361***	0.1707**	0.1240**
	(0.016)	(0.016)	(0.068)	(0.058)	(0.040)	(0.052)	(0.039)	(0.041)	(0.058)	(0.067)	(0.054)
custom	0.1107***	0.1103***	0.0233	0.2122***	0.2344***	0.0461	0.0264	0.1519***	0.2497***	0.0617	0.0718
	(0.018)	(0.018)	(0.074)	(0.067)	(0.046)	(0.049)	(0.046)	(0.047)	(0.062)	(0.084)	(0.058)
Constant	0.4705***	0.4410***	0.4007**	-0.6597***	0.5866***	0.5363***	1.4599***	0.7667***	0.8956***	1.1684***	0.3854***
	(0.042)	(0.043)	(0.199)	(0.137)	(0.122)	(0.140)	(0.117)	(0.146)	(0.171)	(0.222)	(0.131)
Observations	34,121	34,121	2,772	3,308	5,827	4,418	5,289	4,664	2,813	1,627	3,401

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10
Probit estimate

* news-stand comprehend: Publishing, Journalism, Comics, Photo

Table 5 – Marginal effect (all coefficients are significant with a confidence of 99%)

		Internal Social Capital			External Social Capital		
		Margin	95% Confidence Interval		Margin	95% Confidence Interval	
II- Full sample	At mean	.2826338	.2721626	.293105	.2826338	.2721626	.293105
	Plus one-sd	.3465476	.3334695	.3596256	.3311441	.3196966	.3425916
III- Technology	At mean	.1288989	.0983858	.1594121	.1288989	.0983858	.1594121
	Plus one-sd	.1679332	.1295491	.2063173	.150293	.1174672	.1831188
IV- Food	At mean	.1181315	.0949637	.1412993	.1181315	.0949637	.1412993
	Plus one-sd	.1541294	.1236605	.1845984	.1199003	.0955961	.1442044
V- News-stand	At mean	.2488393	.2236554	.2740231	.2488393	.2236554	.2740231
	Plus one-sd	.3090052	.2777838	.3402266	.2957191	.2675082	.32393
VI- Fashion/Design	At mean	.2303412	.2035533	.2571291	.2303412	.2035533	.2571291
	Plus one-sd	.2834354	.2522071	.3146636	.265412	.2363476	.2944764
VII- Film	At mean	.3580805	.3301997	.3859614	.3580805	.3301997	.3859614
	Plus one-sd	.4113693	.3784544	.4442842	.4020392	.3724259	.4316525
VIII- Music	At mean	.3539728	.3243734	.3835722	.3539728	.3243734	.3835722
	Plus one-sd	.4568889	.4152101	.4985676	.395108	.3626332	.4275724
IX- Games	At mean	.3437274	.2985457	.3889091	.3437274	.2985457	.3889091
	Plus one-sd	.4557887	.4025408	.5090366	.350602	.304329	.3968749
X- Dance/Theater	At mean	.3933222	.3413789	.4452654	.3933222	.3413789	.4452654
	Plus one-sd	.4262936	.3691367	.4834505	.4363164	.3823967	.4902361
XI- Art/Craft	At mean	.2217519	.1944244	.2490794	.2217519	.1944244	.2490794
	Plus one-sd	.2485557	.2161152	.2809963	.2341027	.2065849	.2616205

Table 6 – Heterogeneous choice model

VARIABLES	(1) Model
int_soc_cap x Tech	0.0115***
	(4.65)
int_soc_cap x Food	0.0349***
	(4.93)
int_soc_cap x Film	0.0096***
	(4.19)
int_soc_cap x Music	0.0390***
	(5.62)
int_soc_cap x Newsstand	0.0111***
	(7.11)
int_soc_cap x Fashion_Design	0.0165***
	(7.55)
int_soc_cap x Art_Crafts	0.0057**
	(3.10)
int_soc_cap x Games	0.0081***
	(7.25)
ext_soc_cap x Tech	0.00807**
	(2.83)
ext_soc_cap x Food	0.0127**
	(3.15)
ext_soc_cap x Film	0.0073***
	(4.40)
ext_soc_cap x Music	0.0043***
	(3.15)
ext_soc_cap x Newsstand	0.0124***
	(6.91)
ext_soc_cap x Fashion_Desing	0.0059***
	(3.41)
ext_soc_cap x Art_Crafts	0.0094***
	(4.72)
ext_soc_cap x Games	0.0037
	(1.61)
Controls	Yes
lnsigma	
Film	-1.045***
	(-10.17)
Music	-0.849***
	(-7.70)
Food	-0.774***
	(-6.33)
Tech	-1.458***
	(-13.48)
Newsstand	-1.071***
	(-11.23)
Fashion/Design	-1.300***
	(-13.24)
Art/Craft	-1.060***
	(-10.72)
Games	-1.331***
	(-13.03)
Constant	-1.3952***
	(0.118)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10
Heterogeneous choice model