What explains the success of reward-based crowdfunding campaigns as they unfold?

Evidence from the French crowdfunding platform Kisskissbankbank

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Abstract: Using hand-collected data from a French crowdfunding platform, we identify several success factors that backers value when they decide to support reward-based campaigns. We show that these success factors evolve as the campaign unfolds. The first week of the campaign is of particular interest. We validate most of the conclusions drawn for reward-based crowdfunding in the US and we argue that reward-based and equity-based crowdfunding campaigns seem to driven by similar success factors.

***Index Terms*— Crowdfunding, factors, success, binary response models.**

I. Introduction

Crowdfunding (CF) has been expanding rapidly since the beginning of the century. Today, North America accounts for around half of the total funding volume, while Asia and Europe capture around 30% and 20% of the market respectively (Massolution, 2015). There exist various models of CF but the most popular model is reward-based in which backers receive non-monetary incentives, including pre-orders.

In Europe, the UK and France are the two countries with the highest number of CF platforms, with respectively 124 and 95 active platforms operated by CF startups and incumbents at the end of 2014 (Dushnitsky et al., 2016). Per million residents, the Netherlands rank first with around seven platforms. France, Finland, and the UK follow with two active CF platforms per million of residents.

In France, there were 2.6 million backers in 2016 and €629 million were collected by CF platforms, up from €300 million the year before. In spite of France being a major player in the European CF landscape, there has been no empirical study on the success drivers of reward-based CF campaigns in this country. To the best of our knowledge, this holds true at the EU level as well. All the empirical studies in Europe have exclusively focused on equity-based CF in which backers invest money, receive an entitlement to participate in the profits and value of companies, but lose the invested funds if they fail.

The first empirical study on the success factors of CF campaigns is due to Mollick (2014) who uses data from Kickstarter which was launched in 2009 in the US and is today the most famous reward-based platform in the world. Among other things, Mollick shows that signals of good quality explain the success of CF campaigns. Courntey, Dutta and Li (2017) and Parhankangas and Renko (2017) confirm these findings. Success drivers are also related to the internal social capital (Colombo, Franzoni and Rossi-Lamastra, 2015; Butticè, Colombo and Wright (2017) and the community context (Josefy, Dean, Albert and Fitza, 2017).

These studies employ Kickstarter data and it remains to be seen whether the success of reward-based CF campaigns in Europe is driven by the same factors since cultural, social, and legal norms differ between the US and Europe. For example, social influence may vary according to the degree of individualism within a country. According to the theory of social influence, the behavior of backers is expected to be influenced by previous contributors, pointing to herding patterns. However, such influence could be weaker for individualistic backers who may be less sensitive to comments posted on the website by others during the campaign, for example. Risk attitude is also expected to vary across countries, even more so across continents. High risk-averse backers could require a greater number of quality signals or stronger quality signals, all else equal. For example, a given level of participation during the first week could be perceived as an insufficient positive quality signal in countries with a higher degree of risk aversion. The use of European data may therefore shed new light on the success drivers and the dynamics of CF campaigns.

Unfortunately, those empirical studies which rely on European data focus on equity-based CF platforms only. Among them, Agrawal, Catalini, and Goldfarb (2015) study 34 campaigns in the music sector on the bankrupt Dutch SellaBand online platform. Cholakova and Clarysse (2015) analyze the content of 155 surveys completed by people active on the Dutch Symbid platform. Block, Hornuf and Moritz (2017) look at 71 campaigns on two German platforms. Lukkarinen *et al.* (2016) look at 60 campaigns conducted through the Finnish equity-based Invesdor platform.

However, it remains to be seen whether reward-based and equity-based CF campaigns are sensitive to the same success drivers. This question is not trivial since risk

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attitude adopted by the backers is expected to differ substantially between the two forms of CF. On the one hand, reward-based CF often implies a consumption decision with the risk of being disappointed by the final product at the time of delivery. Of course, the delivery may never occur in some cases, but the financial loss is still limited to the order cost. In equity-based CF, the decision is an investment decision before anything else, with the usual upward and downward financial consequences. Information asymmetry is arguably higher in equity-based CF as well, which is therefore expected to attract less risk-averse investors. It may also be the case that investors in equity-based CF are not less risk-averse but require a higher number of quality signals or stronger quality signals, or even both.

To investigate these questions, we use hand-collected data on 160 CF campaigns conducted in 2014 through the French platform KissKissBankBank (KKBB). We show that the success drivers of CF campaigns evolve as the campaigns unfold. The first week of the campaign is of particular interest. We validate most of the conclusions drawn for reward-based CF in the US and find that reward-based and equity-based CF campaigns seem to driven by similar success factors.

II. THEORETICAL FRAMEWORK

By analyzing the success drivers of reward-based CF campaigns, our paper expands research on signaling theory which is mainly concerned with reducing information asymmetries between entrepreneurs and backers.

As explained by Ahlers, Cumming, Günther, and Schweizer (2015), projects are more likely to receive funding when entrepreneurs send observable and credible signals, i.e. signals that are believed to indicate higher venture quality.

Successful projects are also those which alleviate backers' concerns about uncertainty in the project success. When entrepreneurs provide less (accurate) information to the potential backers, the latter are indeed less likely to assess the proposed venture properly. In this respect, Block, Hornuf and Moritz (2017) indicate that signal effectiveness can be improved by sending signals regularly.

Perkins and Hendry (2005) also stress that different receivers are likely to interpret signals differently, in spite of their similar efforts to capture the signal. Signal clarity is therefore another important feature to make the campaign successful.

Finally, the interpretation by other (potential) backers can affect the effectiveness of signals very much. If a certain number of (potential) backers interprets signals in a particular way, this might lead others to mimic their behavior (Connelly et al., 2011).

To capture the various features of signals sent by the campaign founders, we use several variables related to signal quality, such as the presence of a video on the website. The level of uncertainty about the project is taken into account by including several geographical factors and the number of news posted online by the campaign founders, among others. Signal clarity is evaluated, for example, by identifying projects which offer potential backers with a website specifically dedicated to the project description. Finally, signal effectiveness through imitation is assessed by including several variables related to the campaign dynamics observed at the end of the first week. All these variables are described in more details in the next section.

III. DATA

KKBB was launched in 2010 in France. In 2016, it ranked second in terms of the total funding volume with €73 million collected since inception, behind Ulule with its €89 million. Like Kickstarter, KKBB is specialized in non-monetary rewards. For example, backers can pre-order a customized copy of a product or be included in a list of supporters of a social cause. Intrinsic enjoyment is achieved through social reputation, shared identity, or other non-financial benefits. The minimum pledge may be as low as €1.

KKBB has freely chosen to register itself as a CF "intermediary" in France. In France, registration is required by law only when the platform proposes loans or equity stakes.

The platform follows the 'all-or-nothing' (AON) model which is more likely to attract large non-scalable projects than the 'keep-it-all' scheme (Cumming et al., 2014). Under the AON scheme, entrepreneur gets nothing if the funding target is not reached in the stipulated time. Backers get their contribution back in that case.

KKBB offers a large range of projects which belong to the following categories: art, sports & expeditions, design & innovation, green projects, education, movies, food, games, media, print, fashion, music, photography, live performance, and web & tech. The platform exerts a screening of the projects proposed by the entrepreneurs. Certain conditions must be fulfilled. Projects must correspond to a category that the platform favors and be considered as 'serious' initiatives. This excludes personal projects such as organizing fantastic holidays or gargantuan birthday parties.

The variables we consider in the first part of our analysis are indicated in table 1. To take just a few examples, we see that *goal* is distributed between limits ranging from 100 to 60,000 euros, with a cross-sectional average equal to 4,202.48 euros. This figure is very close to the average value that the platform KKBB had calculated in the population of campaigns, i.e. 4,000 euros. There were also around 34 backers on average by campaign and their average pledge was 50.82 euros across campaigns. In Mollick (2014), there were 67 backers with an average pledge of 64.37 US dollars. Note that Mollick only focuses on projects with a funding target of more than 5,000 dollars, arguing that this would make it possible to better compare these campaigns to the funding provided by business angels and other financial institutions. In our analysis, we chose to stick to the reality of CF based on rewards, whose projected funding's median amount is equal to 2,500 euros in our sample.

[Insert Table 1 here]

In addition to Mollick (2014), we analyze the participation of backers at the end of the first week of campaign, taking into account their number, their total pledge, and the percentage of the target funded.

IV. METHODOLOGY

Once theoretical justification is found for the inclusion of candidate explanatory variables, it sometimes happens in empirical studies that all the variables are thrown into a single model without considering the timing at which the information was truly available to the potential backer. To minimize the risk of hindsight bias, we include in the model the only explanatory variables that are truly and directly observable at three different moments in time during the campaign, i.e., at the start of the campaign, after one week, and at the end. This simple procedure forces us to put oneself into the shoes of potential backers whose choices are more likely to depend on what they directly observe at that moment in time. It should help better identify the success drivers *as the campaign unfolds*.

We use four binary response models to identify the success factors of a CF campaign: the linear probability model (LPM), the Logit model, the Probit model, and the Gompit (or extreme value) model.

We apply the general-to-specific methodology to all the above-cited models, at every stage of the analysis. The general-to-specific (or backward) method consists in starting from a general model that includes all the variables, and then eliminating, step by step, the variable whose critical probability is the higher. The procedure ends when all the variables present in the model are significant at a predetermined level, 5% in our case. This method also deals with multicollinearity issues since it removes the most insignificant variables in turn.[2]

To check the robustness of this manual procedure, we apply an automated multi-path General-to-Specific (GETS) modelling approach to the LPM (Escribano and Succarat, 2012). Multi-path GETS can indeed be vastly superior to single-path GETS and other specification search algorithms. As an agnostic approach, note that GETS is also useful when there are several candidate variables capturing the same success factor but no theoretical justification regarding the choice to be made between these variables ex ante.

V. EMPIRICAL RESULTS

We conducted all the relevant diagnostic tests for all models to address potential issues related to multicollinearity, heteroskedasticity, or error term non-normality. We apply White heteroskedasticity-consistent standard errors in the LPM and the Huber/White standard errors in the three other binary response models.

In the tables, the three-star/double-star/single-star symbols denotes significance at 1%, 5%, and 10% respectively. Figures in bold point to variables that remain significant at 5% after applying the GETS approach.

Table 2 shows the results for the LPM. In the first model specification, we include *all* the candidate variables. The results given in the second column of the table show that three variables are statistically significant at 5%: *% past success by category*, *1st week % pledge*, and *comments*. From an economic point of view, an increase by 10 percentage points (%p) in the category past success rate leads to an increase by 6.7%p in the probability of reaching the funding target, all else equal. The *ceteris paribus* effect of the *1st week % funded* variable is even stronger: the probability of success increases by 9.7%p if the percentage of the target funded after the first week increases by 10%p, all else equal. Finally, the probability of the campaign success increases by 22.4%p if there are 10 more comments by backers on the KKBB webpage, all else equal. *Log(goal)* is the only variable which has a negative marginal effect on the probability of success, significant at a 10% level only. Its coefficient indicates that an increase by 100% in the funding target leads to a decrease by 6.3%p in the probability of the campaign being a success, all else equal. We also obtain high positive rates, i.e., 78% for true signals and 95% for false signals.

[Insert Table 2 here]

The automated multi-path GETS search algorithm applied to this model specification confirms that the only three variables left in the specific model at a 5% level are *% past success by category*, *1st week % funded*, and *comments*, as indicated by their coefficient in bold in column 2 of table 2.

Let us now identify the success factors as the campaign unfolds. In the third column of table 2, we only include the variables observable just before the *start* of the campaign. Interestingly, we note that the variable *video* is statistically significant at 1%. If we compare two similar campaigns except that a video has been developed for the first campaign and not for the second one, then the probability of reaching the funding target is estimated to be 22.7%p higher for the first campaign.

Although the variable *% past success by category* is statistically significant at 10% only in the general version, of the model, the automated multi-path GETS approach reveals that it becomes significant at 5% in the specific version, as indicated by its coefficient being in bold in the table.

Let us now position ourselves *a week* after the launch of the campaign. If we add the variables observable a week after to our specific model identified above, we can see in in column 4 of table 2 that two additional variables become significant: *1st week backers* and *1st week % funded*. First, the probability of success of a campaign increases by 11.7%p if there are 10 more backers at the end of the first week, all else equal. Second, the probability of success of a campaign increases by 10.4%p if the percentage of the target funded after the first week increases by 10%p. We note that these two variables remain significant in the

[2] Before applying the GETS method, the highest VIF value across all 'general' models was 5.72, far below 10. In the 'specific' models (after applying GETS), no VIF value was higher than 2.

specific model after applying the multi-path GETS methodology.

The last step in our analysis of the LPM consists into adding the four communication variables observable at the end of the campaign to the specific model identified after a week. *Comments* is the only variable among these four variables, which is statistically significant at 1%. It also remains significant at 5% in the specific model after implementing the GETS approach. Interestingly, its inclusion in the model leads to the exclusion of the *video* variable, which loses its information content.

Table 3 shows the results for the Logit model. The inclusion of *all* the candidate variables in column 2 does lead to similar conclusions as in the LPM. However, we observe than the *log(goal)* variable is statistically significant at 5% (versus 10% only in the LPM). Its marginal effect is nevertheless similar. To compare the Logit coefficients to those of the LPM, we compute the scale factor by averaging the individual partial effects across the sample, which gives us a value of 0.0723. The average partial effect (APE) of *log(goal)* on *success* is therefore equal to -0.0895, implying that an increase by 100% in the funding target leads to a decrease in the probability of the campaign being a success by 8.95%p, all else equal (versus 6.3%p in the LPM). Second, the *video* variable is statistically significant at 10% while it was not significant in the LPM, and its APE is equal to 0.0792 (versus 0.0876 in the LPM). Third, the variable *1st week % funded* is statistically significant at 5% (versus 1% in the LPM) and its APE is equal to 0.0082 (versus 0.0097 in the LPM). Finally, the single-path GETS approach selects two variables at a 5% level (versus three variables in the LPM). The variables *1st week % funded* and *comments* are the only variables remaining in the specific model, as indicated by their coefficient in bold in column 2 of table 3.

[Insert Table 2 here]

Empirical results for the Logit model based only on information observable at the *start* of the campaign, are presented in column 3 of table 3. They confirm the findings obtained by the LPM. Three variables are significant in the general model, i.e., *log(goal)*, *% past success by category*, and *video*. The economic significance of each variable remains similar. For example, using a scale factor equal to 0.2233, we obtain that the APE of *video* is 0.2228, meaning that the probability of reaching the funding target at the end of the campaign is estimated to be 22.28%p higher when there is a video on the KKBB page, all else equal. The coefficient estimate was 22.7%p in the LPM. Applying the GETS method to identify the specific model, we also confirm the results found in the LPM: *log(goal)* is indeed no longer significant at 5%.

A *week* after the launch of the campaign, the Logit model (in column 4 of table 3) leads to the same conclusions as the LPM (in column 4 of table 2). We note that the true and false positive rates increase quite substantially w.r.t. the *start* model, from 51% to 80% and from 71% to 85% respectively. The first week of campaign is therefore very insightful.

If we add the four communication variables observable at the end of the campaign, we obtain the same general model as before. Both the LPM (in column 5 of table 2) and the Logit (in column 5 of table 3) identify three success factors: *% past success by category*, *1st week % funded*, and *comments*. However, the single-path GETS approach leads to the exclusion of *past success by cat. %* while it remained significant at 5% in the LPM.

To save space we do not report the results for the Probit and Gompit models which are fully in line with the Logit model.

VI. CONCLUSION

Using hand-collected data from the French CF platform KKBB, we find that crowdfunders react positively to the presence of a video at the start of a reward-based campaign, which is in line with Mollick (2014), Butticè, Colombo and Wright (2017) and Courntey, Dutta and Li (2017) who all use Kickstarter data.

While geographical factors do not play any role, the past success rate observed by project category before the launch of the campaign does matter, even when additional information becomes available as the campaign unfolds. Colombo, Franzoni and Rossi-Lamastra (2015), Courntey, Dutta and Li (2017) and Mollick (2014) also indicate that the previous success rate in the respective project category matters for reward-based campaign success in the US.

The first week of the campaign is also very informative when it comes to determining its ultimate success, and in particular the percentage of the project's target that is funded after a week. We confirm Colombo, Franzoni and Rossi-Lamastra (2015) who use Kickstarter data and did find that early contributions are crucial for the success of a CF campaign. These results indicate that the campaign can quickly enter into a virtuous or vicious circle.

The success of a campaign also depends on the number of comments left by the backers, showing that opinions, reviews, and shared experiences matter to the crowd, as in Mollick (2014) and Courntey, Dutta and Li (2017) who focus on reward-based CF in the US.

Contrary to Mollick (2014), we do not find evidence that a large numbers of friends on online social networks are associated with success, once we control for participation of backers at the end of the first week of campaign, taking into account their number, their total pledge, and the percentage of the target funded. Neither can we any evidence that geographic and population factors are related to project success in France.

There is robust evidence that crowdfunders seem to prefer to jump onto jam-packed commuting trains rather than on empty stopped trains. In some way, this is no surprise: the success or failure of a CF campaign does depend on what we anticipate the other crowd members' participation will be, implying that CF is also subject to self-fulfilling or self-destructive prophecies.

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Table 1. Description of all the variables

	Mean	***Median***	***Sd***	***Minimum***	***Maximum***
Funding Variables					
Success	0.46	0.00	0.50	0.00	1.00
% past success by category	47.69	48.50	10.20	24.00	64.00
Goal	4,202.5	2,500	6,125.32	100	60,000
Total pledge	2,034.8	877.5	3,183.97	0.00	22,270
% Funded	59.80	36.59	55.29	0.00	232.80
Backers	33.88	17.00	52.69	0.00	460.00
Pledge/backer	50.81	39.36	47.31	0.00	375.00
1st week backers	8.28	5.00	12.61	0.00	115.00
1st week total pledge	376.94	150	759.24	0.00	7,185.00
1st week % funded	13.82	7.23	19.71	0.00	137.69
Geography Variables					
France	0.84	1.00	0.36	0.00	1.00
Density	6818.11	3478.00	8206.95	25	21322.00
LocalPCI/FrPCI %	109.69	100	52.13	1.07	277.81
LocalPop/FrPop %	1.16	0.20	1.92	0.12	12.83
Design Variables					
Photos	0.91	1.00	0.29	0.00	1.00
Video	0.52	1.00	0.50	0.00	1.00
Website	0.67	1.00	0.47	0.00	1.00
Communication Variables					
Updates	2.36	1.00	4.35	0.00	27.00
Comments	7.56	3.00	10.20	0.00	58.00
Facebook friends	698.11	129.00	2,099.22	0.00	22,000.00
Shares	251.97	101.00	463.43	0.00	3,412.00

Success = 1 if *total pledge* (i.e. total amount actually pledged) has reached or exceeded *goal* (i.e. funding target), 0 otherwise. *% past success by category* = success rate observed in each category before the launch of the campaign. *% funded* = percentage of the target funded at the end of the campaign = (*total pledge* / *goal*)*100. *Backers* = number of contributors. *Pledge/backer* = average pledge by backer. *1st week backers* = number of backers at end of first week. *1st week total pledge* = total pledge of backers at end of first week. *1st week % funded* = percentage of the target funded at end of first week. *France* = 1 if the campaign is located in Metropolitan France, 0 otherwise. *Density* = number of inhabitants per km^2 in the city from which the project is launched. *LocalPCI/FrPCI %* = ratio in % of income per capita in the city from which the project is launched divided by income per capita in France. *LocalPop/FrPop %* = ratio in % between population in the city from which the project is launched and population in France. *Photos* / *video* = 1 if there is at least one photo / video on the project description webpage, 0 otherwise. *Website* = 1 if there a website specifically dedicated to the project, 0 otherwise. *Updates* = number of news posted online by the entrepreneur on the project page. *Comments* = number of comments posted online by the backers on the project page. *Facebook friends* = number of Facebook friends. S*hares* = number of shares on Facebook, Twitter and Google+.

Table 2. Probability Linear Model (Dependent variable: *Success*)

	(All)	***(Start)***	***(1Week)***	***(End)***
Constant	0.2904	0.3061	48.50	10.20
Funding				
Log(goal)	-0.0630*	-0.0634*		
Past success by cat. %	**0.0067****	**0.0073***	**0.0081*****	**0.0069****
1st week backers	-0.0032		**0.0117****	-0.0048
1st week total pledge	2.39E-06		-5.30E-05	
1st week % funded	**0.0097*****		**0.0104*****	**0.0112*****
Geography				
France	0.0256	0.0353		
Density	1.66E-06	5.96E-06		
LocalPCI/FrPCI %	5.96E-05	0.0003		
LocalPop/FrPop %	0.0112	0.0083		
Design				
Photos	-0.0508	0.1110		
Video	0.0876	**0.2270*****	**0.1415****	0.0682
Website	-0.0361	-0.0106		
Communication				
Updates	0.0143			0.0129
Comments	**0.0224*****			**0.0217*****
Facebook friends	5.82E-06			3.66E-06
Shares	3.51E-05			3.98E-05
Adj. R-squared (%)	47.22	4.74	34.31	48.06
True positive rate (sensitivity)	78.38	52.70	60.81	72.97
False positive rate (specificity)	95.35	72.09	91.86	96.51

Variables are defined in Table 1. Fixed effects for the project categories were included in all regressions, but their estimated coefficients are not reported to save space. None of them was statistically significant, even after applying the multi-path GETS methodology.

Table 3. Logit Model (Dependent variable: *Success*)

	(All)	***(Start)***	***(1Week)***	***(End)***
Constant	1.7353	-0.7636	-5.3784	-6.4107
Funding				
Log(goal)	-1.2378**	-0.2920*		
Past success by cat. %	0.0636**	**0.0326***	**0.0454****	0.0524**
1st week backers	0.1284		**0.2000*****	0.0469
1st week total pledge	0.0028		-0.0008	
1st week % funded	**0.1130****		**0.1601*****	**0.1815*****
Geography				
France	0.8080	0.1299		
Density	-4.01E-05	2.70E-05		
LocalPCI/FrPCI %	0.0019	0.0013		
LocalPop/FrPop %	-0.0269	-0.0378		
Design				
Photos	-0.9145	0.4944		
Video	1.0962*	**0.9982*****	0.7755	
Website	-0.5099	-0.0475		
Communication				
Updates	0.1233			0.0887
Comments	**0.2728*****			**0.2433*****
Facebook friends	-5.38E-05			3.69E-06
Shares	0.0005			5.99E-05
McFadden R-squared (%)	65.94	7.70	48.18	61.71
True positive rate (sensitivity)	86.49	51.35	79.73	82.43
False positive rate (specificity)	92.85	70.93	84.88	92.85

Variables are defined in Table 1. Fixed effects for the project categories were included in all regressions, but their estimated coefficients are not reported to save space. None of them was statistically significant, even after applying the GETS methodology.