OVERCHOICE AND FUNDING FOR ENTREPRENEURIAL VENTURES *

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Abstract

In this study we focus attention on funding for entrepreneurial ventures using crowdfunding. In particular, we investigate reward options and their effects on the likelihood of success of fundraising. We argue that, as they provide more choices to backers, the number of reward options improves the likelihood of success but, consistent with behavioral economic literature, leads to backer overchoice. Our analysis confirms these predictions and show that the relationship between success and the number of reward options is concave, thus, supporting the consumer overchoice theory. In addition, we predict that the price of these options should negatively affect the likelihood of the success due to the high uncertainty surrounding crowdfunding (for example, whether the promised product is delivered at all, has the promised features, or be delivered within the promised time frame). We also posit that due to their lower perceived risk, the relationship between probability of success of and average option price should be less negative for US projects than other countries. Our analysis confirms these predictions and demonstrates a negative relationship between average reward option price and probability of success, which is less negative for US projects than other countries.

OVERCHOICE AND FUNDING FOR ENTREPRENEURIAL VENTURES

1. Introduction

In this paper we focus attention on funding for entrepreneurial ventures through crowdfunding. Crowdfunding, a form of crowdsourcing, has gained popularity in recent period. The term "crowdfunding" is used to describe financing of entrepreneurial projects by raising funds from a large group of people, commonly referred to as backers. Contrary to common wisdom, crowdfunding has been around for a long time. An early example of a crowdfunding campaign is the funding of the Statue of Liberty in 1885 (Harrison, 2013), which raised $101,091 from more than 160,000 donors following a newspaper campaign. The donors included people from all walks of life including children, street cleaners, business people, and politicians, with the vast majority of the donations being less than a dollar.

Crowdfunding is commonly partitioned into reward- , debt-, and equity-based[1].Reward-based crowdfunding (e.g., on Kickstarter) entails contributions by backers in exchange for a tangible reward (e.g., a physical or a digital product). The project's creators also provide a list of possible donations and related rewards per each donation.

This study examines a sample of 92,419 Kickstarter projects that were launched between 2013 and 2015, raising about $0.9B (please see Table 1 below for summary statistics). Kickstarter is one of the most popular and successful reward-based platforms, and has been used in several studies on crowdfunding (e.g., Colombo et al., 2015, Buttice at al., 2017, Courtney et al., 2017, Kuppuswamy and Bayus, 2017, and Mollick, 2014)[2]. According to Kickstarter (2017),

[1] The difference between reward- and equity-based are discussed in several studies (see, for example, Cholakova & Clarysse, 2015) and in the Institutional Background Section.
[2] Another popular rewards-based crowdfunding platforms is Indiegogo. However, we do not have access to their data

369,000 projects were launched on the platform, 131,000 of which have been successful, raising about $2.86B. The types of the projects launched on Kickstarter vary from art to technology.

The study contributes to the extant literature by adding several dimensions that are scarcely investigated in the literature. One contribution of this study is the examination of the effects of the number of donation options offered by projects, and the average reward price, on the probability of crowdfunding success. As this study demonstrates, they are quite significant across the countries studied and all categories, in determining the likelihood of project success.

Moreover, this study contributes to the behavioral economics literature on consumers' overchoice effects (Iyengar and Lepper, 2000, Iyengar, 2004, Gourville and Soman, 2005) by analyzing the concavity of the relation between the number of reward options and probability of success. The overchoice literature asserts that, when faced with a large number of product options, consumers experience less satisfaction, and buy less.

Another contribution of this study is its analysis of perceived risk due to location (the project's country of origin) and the probability of success. Mollick (2014) examines how geography matters for project Kickstarter success but, in contrast with this study, looks at US projects only. In particular, we compare projects originating in the US, other G7 countries, OECD countries other than G7, and non-OECD countries.

The research question that we analyze in this paper are as follows:

1. What are the effects of the number of reward options, and their average price, on the project's probability of success?
2. Are there overchoice effects for the number of reward options?

3. Do backers perceive the risk embedded in reward options to be the same for projects from the US and elsewhere?

Section 2 of this study describes the theoretical background and the research hypotheses and; Section 3 provides a description of the data used: Section 4 provides analysis of results; concluding remarks are offered in Section 5.

2. Theoretical Background and Research Hypotheses

Behavioral economics research demonstrates the overchoice phenomenon when consumers are faced with a large number of alternatives. Iyengar and Lepper (2000) challenge the conventional wisdom that having more choice is necessarily more intrinsically motivating than having less options. The study demonstrates that people are more likely to purchase exotic jams or gourmet chocolates, and undertake optional class essay assignments, when offered a limited array of 6 choices rather than an extensive array of 24 or 30 choices. Furthermore, participants in the experiments report greater satisfaction with their choices, and write better essays, under a limited set of options than an expanded one. Consistent with this idea, Iyengar (2004) analyzes employees' decisions about whether to invest in 401(k) retirement savings plans and finds that as the number of fund options increase, employee 401(k) participation rates decrease. Gourville and Soman (2005) distinguish between alignable and non-alignable assortment types for consumer choices. An "alignable" assortment is defined as a set of brand variants that differ along a single, compensatory dimension and, hence, choosing from that assortment only requires within-attribute trade-offs. In contrast, a "nonalignable" assortment is defined as a set of brand variants that simultaneously vary along multiple, noncompensatory dimensions, demanding between-attribute tradeoffs. The study shows that increasing a brand

non-alignable product assortment, or variety, can lead to overchoice by consumers as it increases both their cognitive effort and the potential for regret, thereby decreasing brand share.

We argue that providing a number of alternative donations, and related rewards, to backers is, in essence, the same as product assortment and, hence, would lead to consumers' overchoice. Consequently, consistent with the literature on overchoice we argue that the probability of success as a function of reward options is concave, i.e., it will increase in the number of options in increasing increments up to a point, then show diminishing marginal rates, and finally will have no effect on success or even decrease it (Iyengar and Lepper, 2000, Iyengar, 2004, Gourville and Soman, 2005)[3]. Consequently, we predict the following:

Hypothesis 1a: Regardless of the project category, and its country, the probability of success for crowdfunding campaigns increases in the number of reward options up to a certain limit.

Hypothesis 1b: Regardless of the project category, and its country, the probability of success for crowdfunding campaigns, as a function of the number of reward options, is concave.

As the result of high uncertainty associated with crowdfunding projects we can expect that the higher the average donation (average reward option price) the less likely it is to receive funding from potential backers because, while they are willing to invest in uncertain projects, backers will not risk a large amount. As such, ceteris paribus, the likelihood of success for crowdfunding campaigns should decrease in the average reward option price.

[3] Another possible reason behind this result is that projects with many reward options, or only one option, could be related to unsophisticated plans by the founders. Consequently, endogeneity could be the driving force for these reward options number extremes. One way that we can rule this out is to apply winsorizing as part of robustness tests and see whether these results hold when we limit extreme values.

Hypothesis 2: Regardless of the project category, and its country, the probability of crowdfunding campaigns decreases in the average price of reward options.

Prior research has shown that geography matters for the likelihood of success of US Kickstarter projects (e.g., Mollick, 2014). As such, we propose extending this idea to include non-US projects. In particular, we compare between projects originating in the US, and other countries. As Kickstarter is essentially a US centric website, extending the idea of Mollick (2014) ensues in having a lower perceived risk by backers of US projects, translating to the next hypothesis:

Hypothesis 3: Reward options are perceived to be less risky for US projects than those from other countries.

Prior research has also demonstrates that backers behavior, and in turn, projects' success is a function of the Kickstarter category that they are listed in, and a function of whether the founder is a serial entrepreneur (e.g., Mollick, 2014, Courtney et al., 2017, Colombo et al., 2015, Butticè et al., 2017, Skirnevskiy et al., 2017). Consequently, we control for the categories of the projects, the project's country of origin, and serial entrepreneurs when we test for the likelihood of success.

Variables

$Success$, the dependent variable in our model, is defined (and reported by Kickstarter) as achieving the stated funding goal. Since success in Kickstarter is "an all or nothing" proposition (Mollick, 2014) it is a dichotomous variable, as commonly used in the literature (e.g., Colombo et al., 2015, Josephy et al., 2017, Butticè et al., 2017)

$Goal$ is the goal of the campaign. Similar to the literature we expect this variable to have a negative coefficient (Mollick, 2014, Colombo et al., 2015, Butticè et al., 2017), i.e., it negatively affects the probability of success.

$Comments\ Count$ is the number of comments left by backers during the active campaign. Consistent with other studies in this area we expect this variable to have a positive coefficient (Mollick, 2014, Courtney et al., 2017). In other words, more comments improve the probability of success.

$Duration$ is the time period for which the campaign is active. Consistent with other studies in this area we expect this variable to have a negative coefficient (Mollick, 2014, Colombo et al., 2015, Skirnevskiy et al., 2017, Courtney et al., 2017, Butticè et al., 2017). In other words, this variable negatively affects the probability of success.

$Reward\ Options$ is the number of donation options. Based on Hypothesis 1a, we expect this variable to have a positive coefficient and, moreover, exhibit a concave relationship with success. In other words, having more donation options improves the probability of success but could lead to overchoice effects.

$Average\ Option\ Price$ is the average price of reward options. Based on Hypothesis 2, we expect this variable to have a negative coefficient, (i.e., it negatively affects the probability of success).

$US\ Dummy$ is an indicator variable indicating a U.S. project, which is then used to create the following interaction (slope dummy) variables: $US\ Dummy * \mathrm{Log}(goal),\ US\ Dummy * Comments\ Count,\ US\ Dummy * Duration, US\ Dummy * Reward\ Options, US\ Dummy * Avg.\ Option\ Price.$

Models

Using a logistic regression, Model (A) below tests Hypothesis 1a, controlling for categories, country of the project origin, and serial entrepreneurs. The categories that we used are the same as the ones used by Kickstarter, and include Art, Crafts, Comics, Dance, Design, Fashion, Food, Film & Video, Games, Journalism, Music, Photography, Technology, Theater, and Publishing . Note that, consistent with the literature (e.g., Colombo et al., 2015, Josephy et al., 2017), we use the logarithm of the campaign's goal, $\text{Log}(Goal)$.

$$\begin{aligned} Success = \propto & + \beta_1 \text{Log}(Goal) + \beta_2 Comments\ Count + \beta_3\ Duration \\ & + \beta_4\ Reward\ Options + \beta_5\ Median\ Option\ Price \\ & + \gamma_1 [US\ Dummy * \text{Log}(Goal)] + \gamma_2 [US\ Dummy * Comments\ Count] \quad \text{(A)} \\ & + \gamma_3 [US\ Dummy * Duration] + \gamma_4 [US\ Dummy * Reward\ Options] \\ & + \gamma_5 [US\ Dummy * Average\ Option\ Price] + \varepsilon \end{aligned}$$

In order to test for Hypothesis 1b, using a logistic regression, we analyze model B below separately for the following reward options number groups to test for the concavity of success as a function of the number of reward options: the lowest quartile of the reward options number (1-3 reward options), the second quartile of the reward options number (4-6 reward options), the third quartile of the reward options number (7-11), and two sets from the fourth quartile (12-25 and 26 and above)[4].

[4] The breakdown of the fourth reward options quartile into two groups is necessary to obtain the point at which the reward options stops affecting the probability of success, or even becomes negative.

$$
\begin{aligned}
Success = \propto_i &+ \beta_{1i}\,\mathrm{Log}(Goal) + \beta_{2i} Comments\ Count + \beta_{3i}\ Duration \\
&+ \beta_{4i}\ Reward\ Options + \beta_{5i}\ \ Avearge\ Option\ Price \\
&+ \gamma_{1i}[US\ Dummy * \mathrm{Log}(Goal)] \\
&+ \gamma_{2i}[US\ Dummy * Comments\ Count] \qquad \text{(B)} \\
&+ \gamma_{3i}[US\ Dummy * Duration] \\
&+ \gamma_{4i}[US\ Dummy * Reward\ Options] \\
&+ \gamma_{5i}[US\ Dummy * Average\ Option\ Price] + \varepsilon,\ \mathrm{i} = 1,2,3,4,5
\end{aligned}
$$

We test whether Model (B) is diagnostically superior to Model (A) we use receiver operating characteristic curves (ROC). In essence, the ROC curve compares the rates of true positives (known also as sensitivity, or recall), false positives, false negatives, and true negatives (known also as specificity) between regression models (Pepe et al., 2010).

In order to test Hypothesis 2 we analyze the coefficients of Average Price in Models (A) and (B) above, in particular, whether they are negative and significant.

In order to test Hypothesis 3 we examine whether the coefficients of the US average option price interaction are positive and significant, thus, indicating that reward options are perceived to be less risky for US than non-US projects.

3. Data

Kickstarter is one of the more popular crowdfunding platforms and has been commonly used for studies of rewards-based crowdfunding (Colombo et al., 2015, Buttice at al., 2017, Courtney et al., 2017, Kuppuswamy and Bayus, 2017, and Mollick, 2014). Using C# and Pyton based supervised artificial intelligence algorithms that were fed by web crawlers, we extracted from the Kickstarter website information about 109,107 projects launched from March 2013 to

May 2016. Dropping observations that are missing data yields 108,034 projects[5]. The data from 2013 to 2015 (92,230 observations) is used for model estimation, and the data from 2016 (15,804 observations) is used to analyze out-of-sample validation.

The descriptive statistics are provided in Table 1 below. As Table 1, panel A, shows most of the observations in our sample come from the US (68,648 projects), followed by other G7 countries (15,420 projects), non G-7 OECD countries (6,584 projects), and the balance from non-OECD countries (1,767 projects). The success rate was the highest for US projects (47.2%), followed by non-OECD projects (46.01%), G-7 projects other the US (43.2%) and OECD projects from non G-7 countries (33.94%). The success rate for US projects was significantly higher than those from either the rest of the G-7, or non G-7 OECD countries. Similarly, the success rate for projects from G-7 countries, other than the US, was significantly higher than those from the rest of OECD. In contrast, the difference between the success rate of non-OECD countries and those from US, or non-US G-7 countries, is not statistically significant. Interestingly, non-OECD projects had a statistically significant higher rate of success than those from OECD countries that are not in the G-7.

Panel B provides the descriptive statistics with respect to the explanatory variables. It is interesting to note that the projects in our sample provide on average 8 reward options (spanning

[5] The use of artificial intelligence algorithms is necessary because some of the fields on the Kickstarter website appear as text data while others appear as pictures. To further complicate the data collection, Kickstarter regularly changes the structure of the fields. Furthermore, from April 2015 Kickstarter began to limit how many projects can be viewed in a single category. As such, algorithms are needed in order to extract dynamic data, translate the graphic fields into text, and to convert all the currencies for non-US projects to US dollars. Specifically, we first used the exposed JavaScript Object Notation (JSON) application programming interface (API), and then each page was processed by using the API project index. Finally an Internet bot (also known as a web robot) was used to convert the currencies for non-US projects into US dollars using the exchange rate that prevailed during the project's duration.

between one option and 227), and the mean average reward price is $272.49 (the two extremes are $0.73 and $31,328)[6].

Table 1 - Desciptive Statistics

A. Countries represented

All projects by country/group

	US	Non-US G7 Countries	Non-G7 OECD Countries	Non-OECD Countries	All countries
Observations	68,648	15,420	6,584	1,767	92,419
Success Rate	0.472	0.432	0.3394	0.4601	0.455
Std.Dev. Success Rate	0.499	0.496	0.473	0.499	0.498

Differences in Success Rates

Two-sample t test with unequal variances of differences in success rates (column-row)

	US	Non-US G7 Countries	Non-G7 OECD Countries	Non-OECD Countries
US	0			
Non-US G7 Countries	9.0393***	0		
Non-G7 OECD Countries	21.6224***	13.1041***	0	
Non-OECD Countries	0.9898	2.2435**	9.1267***	0

*** p<0.01, ** p<0.05, * p<0.1

B. Variables

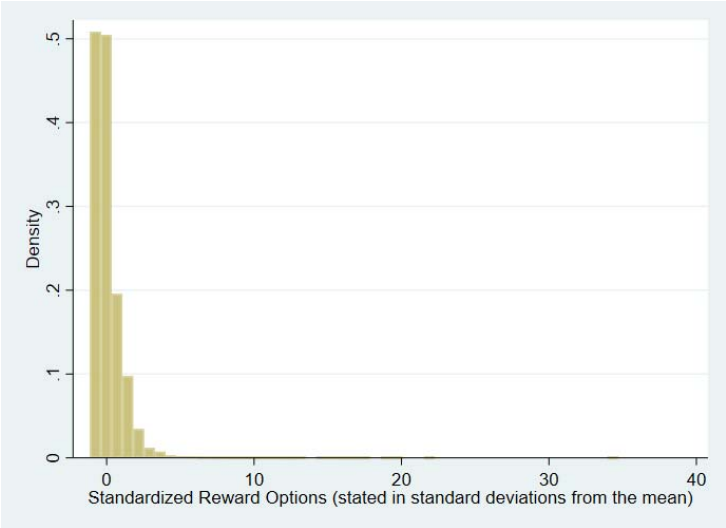
Variable	Obs	Mean	Std. Dev.	Min	Max	[95% Conf. Interval]	
Goal	92,419	50,713.01	1,328,327.00	0.60	1.51E+08	42,148.98	59,277.04
Pledged	92,419	11,266.42	84,680.78	0.00	8,782,572	10,720.46	11,812.37
Comments Count	92,419	54.36	1,750.79	0.00	382,547	43.07	65.64
Duration	92,419	32.67	11.08	1.00	89	32.60	32.74
Reward Options	92,419	8.18	6.31	1.00	227	8.14	8.22
Average Option Price	92,419	272.49	566.20	0.75	31,328	268.84	276.14

Figure 1 below provided the histogram for the standardized reward options (related to the reward options that are distributed, as Table 1 Panel B shows, and between 1 and 227), where the x axis is stated in standard deviations from the mean, which shows as 0 (transformed from the

[6] Interestingly, the average median reward is only $82.44 (ranging between $0.73 and $10,000).

raw mean of 8.18 reward options). The figure demonstrates that the number of reward options is skewed to the left, thus, showing the preference of founders for lower number of rewards.

Figure 1- Histogram of Standardized Reward Options



In order to avoid a scaling problem with the average reward option price, which are distributed between $0.73 and $31,327.71, (see Table 1 panel B), a histogram is plotted for the logarithm of average option price, as depicted in Figure 2 below:

Figure 2- Histogram of Log(Average Option Price)

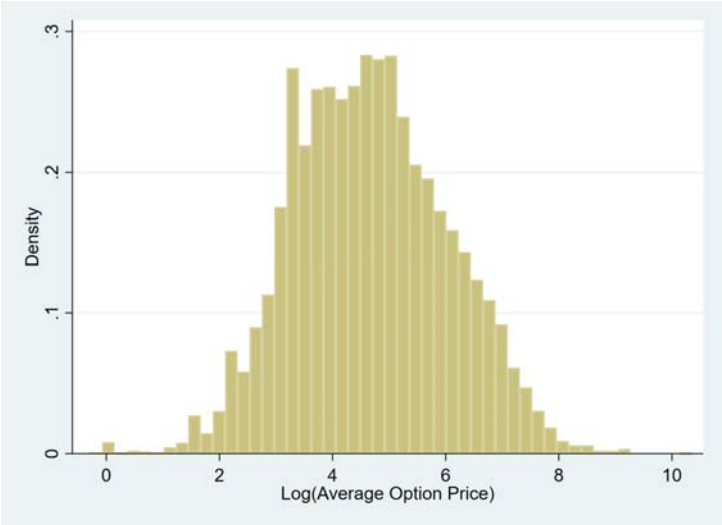


Table 2 provides the correlation matrix. As expected, the correlations matrix shows that success is negatively correlated with the goal of the campaign, its duration and average option price. On the other hand, success, as expected, is positively correlated with the amount pledged, the comments count, and the number of reward options.

Table 2 –Correlation Matrix

	Success	Goal	Pledged	Duration	Duration	Reward Options	Average Option Price
Success	1						
Goal	-0.0277*	1					
Pledged	0.1285*	0.0079*	1				
Comments Count	0.0330*	0.0058	0.5476*	1			
Duration	-0.1588*	0.0227*	0.0109*	-0.0041	1		
Reward Options	0.3268*	-0.0112*	0.1455*	0.0401*	-0.0157*	1	
Average Option Price	-0.1105*	0.0974*	0.1169*	0.0624*	0.0826*	0.0781*	1

* $p<0.05$

4. Results

We report the results of Model A in Table 3 below. These results show that, consistent with the discussion in Section 4 above, the coefficients of *Log(Goal)*, *Comments Count*, and *Duration* have the same signs as we expected, and are highly significant. Consequently, the model indicates that the probability of crowdfunding success is negatively affected by the goal of the campaign and its duration, and improves with the number of comments on the project. Moreover, consistent with Hypothesis 1a, the sign of the *Reward Options* coefficient is positive and highly significant. Therefore, showing, as predicted, the strong positive effect of the number of reward options on the likelihood of crowdfunding success. Also, consistent with Hypothesis 2, the sign of the *Average Option Price* coefficient is negative and highly significant. Therefore, demonstrating, as predicted, a strong negative effect of the average reward option price on the likelihood of crowdfunding success. The US interaction variable with *Log*(*Goal*) does not provide any incremental significant effect for the US. On the other hand, US interaction variables

show that *Duration* has an incremental significantly negative impact on success for US projects, while the number of reward options has a significantly positive incremental effect for US projects. Consistent with Hypothesis 3 the US interaction variable with *Average Option Price* is positive and highly significant, thus indicating that reward options are perceived to be less risky for US projects than those from other countries.

Table 3 - Tests of Model A (No Concavity Assumed)

Number of Reward Options	All
VARIABLES	Success
Log(Goal)	-0.458***
	(-33.66)
Comments Count	0.0399***
	(6.289)
Duration	-0.0176***
	(-12.23)
Reward Options	0.172***
	(31.37)
Average Option Price	-0.000924***
	(-13.96)
US Dummy	0.186
	(1.435)
US Dummy*Log(Goal)	-0.00934
	(-0.564)
US Dummy * Comments Count	0.0372***
	(2.988)
US Dummy * Duration	-0.00566***
	(-3.268)
US Dummy * Reward Options	0.0246***
	(3.573)
US Dummy * Average Option Price	0.000238***
	(3.176)
Constant	2.618***
	(24.47)
Observations	92,230
Wald Chi2	8927
p	0
Log pseudolikelihood	-46115
McFadden Pseudo R-squared	0.275
Country controls	Yes
Category controls	Yes
Serial entrepreneur controls	Yes

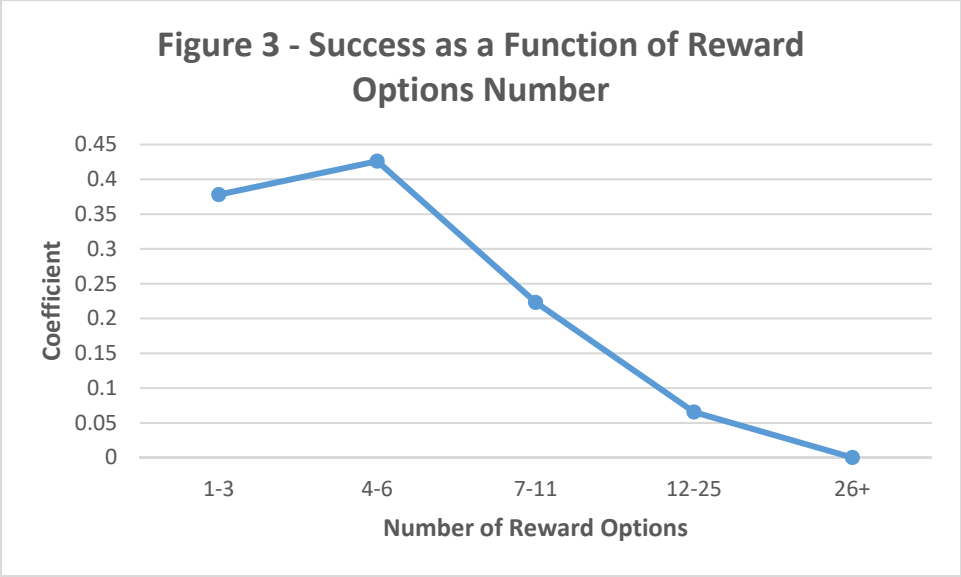
Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We report the results of Model B in Table 4 below. Consistent with the discussion in section 4 above, the coefficient of the *Log(Goal)* coefficient is negative and significant for all reward options quintiles. The coefficients of *Comments Count* and *Duration* all have the predicted signs but are highly significant only when the number of reward options is 25 or less, perhaps due to the overchoice effect. Consistent with Propositions 1a and 1b, the relation between success and the number of reward options, as depicted in Figure 3 below, is an increasing concave function, thus, demonstrating a overchoice effect for backers (Iyengar and Lepper, 2000, Iyengar, 2004, Gourville and Soman, 2005). As such, the coefficient of *Reward Options* is 0.378 in model 1 (1-3 reward options), goes to 0.426 in model 2 (4-6 reward options), then to 0.223 in model 3 (7-11 reward options), 0.0654 in model 4 (12-25 reward options), and finally 0.0212 in model 5 (over 25 reward options). Moreover, these coefficients are highly significant for models 1-4 but not significant in model 5, the one with the extremely high number of reward options. Interestingly, the US interaction variable with *Reward Options* is negative and significant (weakly) for model 5 (26+ options), ensuing in a negative coefficient for US projects that have over 25 reward options, thus, lending support for a stronger overchoice effect for US projects than other countries. These results also show the relation between *Success* and *Reward Options* for US projects is the same as other countries for projects that have 25 or less options. Consistent with Hypothesis 2, the probability of crowdfunding campaigns decreases in the average price of reward options, as indicated by the highly significant negative coefficient of Average *Option Price*. The coefficients of the US interaction variable with *Average Option Price* are all positive, as predicted in Proposition 3. They are, however, only weakly significant for Models 1 and 3 and not significant for the other models. In summary, overall these results are consistent with Hypotheses 1a, 1b, 2 and 3.

Table 4 - Tests of Model B (Concavity Assumed)

Number of Reward Options	1-3	4-6	7-11	12-25	≥26
	(1)	(2)	(3)	(4)	(5)
VARIABLES	StateDum	StateDum	StateDum	StateDum	StateDum
Log(Goal)	-0.599***	-0.511***	-0.529***	-0.557***	-0.516***
	(-21.57)	(-20.88)	(-18.90)	(-12.37)	(-3.981)
Comments Count	0.329***	0.137***	0.0696***	0.0160***	0.00583
	(2.854)	(4.462)	(7.280)	(4.420)	(1.165)
Duration	-0.0150***	-0.0149***	-0.0254***	-0.0201***	0.00878
	(-3.918)	(-5.523)	(-9.270)	(-5.002)	(0.527)
Reward Options	0.378***	0.426***	0.223***	0.0654***	0.0212
	(6.832)	(11.10)	(10.84)	(5.407)	(1.630)
Average Option Price	-0.00171***	-0.00150***	-0.000921***	-0.000552***	-0.000900**
	(-4.033)	(-8.290)	(-8.813)	(-3.830)	(-2.369)
US Dummy	0.143	0.530*	0.390	0.0826	1.192
	(0.473)	(1.730)	(1.159)	(0.173)	(0.717)
US Dummy*Log(Goal)	-0.0583*	-0.0239	0.0250	0.0760	0.0732
	(-1.669)	(-0.822)	(0.714)	(1.463)	(0.474)
US Dummy * Comments Count	0.261*	0.0556	0.00604	0.0154**	0.0573***
	(1.919)	(1.406)	(0.303)	(2.155)	(3.663)
US Dummy * Duration	-0.00495	-0.00752**	-0.00309	-0.00612	-0.0340*
	(-1.026)	(-2.287)	(-0.961)	(-1.320)	(-1.831)
US Dummy * Reward Options	0.0776	-7.71e-07	-0.0218	-0.0144	-0.0252*
	(1.148)	(-1.70e-05)	(-0.911)	(-1.049)	(-1.753)
US Dummy * Average Option Price	0.000850*	0.000298	0.000195*	-4.00e-05	-0.000218
	(1.692)	(1.400)	(1.660)	(-0.254)	(-0.475)
Constant	2.358***	1.581***	3.268***	5.158***	5.080***
	(9.956)	(6.136)	(11.98)	(12.54)	(3.593)
Observations	18,990	23,142	30,521	17,950	1,627
Wald Chi2	1948	2691	3146	1556	169.3
p	0	0	0	0	0
Log pseudolikelihood	-5416	-11335	-16531	-9079	-598.1
McFadden Pseudo R-squared	0.326	0.257	0.212	0.183	0.277
Country controls	Yes	Yes	Yes	Yes	Yes
Category controls	Yes	Yes	Yes	Yes	Yes
Serial entrepreneur controls	Yes	Yes	Yes	Yes	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1



We report the results of the out-of-sample validation, and the comparison between models A and B in Table 5 below. Panel A shows that the diagnostic ability of model B is significantly higher than model A, as shown by larger area under model B's ROC curve (0.8451) than A's (0.8392). Moreover, as Panel A demonstrates the difference between these two ROC curves is highly significant.

Consistent with the discussion above, Panel B in Table 5 shows that at the probability cutoff where Sensitivity and Specificity intersect, i.e., the point at which the rate of true positives is equal to the true negatives rate, is 47.25% for model B (the one embedding overchoice effects) and 43.5% for model A. At these cutoff points model B predicts accurately 76% of successes and failures, while model B predicts 75% of successes and failures[7].

[7] Model A would accurately predict only 70% of successes and 79% of failures at the 47.25% cutoff point while Model B would predict accurately 80% of successes and 72% of failures at the 43.5% probability cutoff point.

Table 5 - Out-Of-Sample Validation

A) ROC Curve Comparison

	Obs	Area	Std. Err.	[95% Conf. Interval]	
Model B (Concavity)	15,804	0.8451	0.0031	0.83909	0.85109
Model A (No Concavity)	15,804	0.8392	0.0031	0.83307	0.84532

Ho: area(Model A) = area(Model B)
chi2(1) = 23.29 Prob>chi2 = 0.0000

B) Out-Of-Sample Estimation Of Success And Failure At The Probability Cutoff Where Sensitivity And Specificity Intresect

Probability Cutoff	47.25%	43.5%
	Model (B)	Model (A)
Actual Successful Campaigns	5,286	5,286
Predicted Success	4,004	3,959
Correct Identification	76%	75%
Actual Unsuccessful Campaigns	10,521	10,521
Predicted Lack of Success	7,951	7,937
Correct Identification	76%	75%

Robustness Tests

Robustness tests that we have conducted include the use of different definitions for the variables. For example, we have used the actual goal of the campaigns instead of Log(Goal), median option price instead of average option prices, and the log of reward options instead of their number. All of these alternative definitions yield almost identical results to the ones above. In addition, we conducted tests for time subsets of our sample (e.g., dropping the 2013 observations). The results of these tests were again almost identical to the results above.

Other robustness tests include using a finer breakdown of projects' countries into US, G-7, OECD and non-OECD groupings, and creating interaction variables for all of those. The results of these tests are almost identical to the results above.

Finally, we have conducted winsorizing tests to examine whether the results hold when we limit extreme reward options numbers. These tests help rule out the endogeneity explanation

of extreme values, i.e., that projects that have only one reward option, or a large number of reward options relate to unsophisticated plan by the founders. Our results show that winsorizing the number of reward options had no effect on the results.

5. Concluding Remarks

This study contributes to the crowdfunding literature by examining the notion that crowdfunding rewards are in essence product assortment, leading to interesting insights beyond the extant literature on the determinants of crowdfunding success. This analysis indicates that the number of these options, and their prices, should be critical to potential backers in their decisions whether to fund a project or not. Specifically, we argue that the number of these options should improve the likelihood of the project's success but could lead to consumer overchoice effects (Iyengar and Lepper , 2000, Iyengar, 2004, Gourville and Soman, 2005). Furthermore, we suggest that the price of these options should negatively affect the likelihood of the project's success because backers would be willing to pay for relatively cheap rewards but not expensive ones due to the high uncertainty embedded in crowdfunding projects. This uncertainty stems from the question of whether the promised product would be delivered at all, would it have the promised features, and whether it would be delivered within the promised time frame (Courtney et al., 2017). Our analysis confirms the importance of these aspects reward alternatives for crowdfunding success.

The idea of reward alternatives and uncertainty effects also leads to insights on the effects of the perceived risk due to the project's country of origin on the success of the campaign. Extending the ideas of Mollick (2013) on the effects of geographical distances on crowdfunding success, we posit that due to their lower perceived risk, the relationship between the probability

of success of US projects and average option price should be less negative than for projects from elsewhere. Our analysis confirms this idea.

One limitation of this study is that it does not explicitly look at the differential effects of serial vs non-serial entrepreneurs on real option pricing. The study can be thus extended by examining whether projects from successful serial entrepreneurs (Butticè et al., 2017), i.e., ones who can credibly signal that their projects embed lower uncertainty than other projects, based on the ideas above, will have less negative relation between success and average option price than projects launched by non-serial entrepreneurs.

Another limitation of this study is that we take the country of origin reported in the projects at face value but since reward-based crowdfunding takes place in an unregulated market, entrepreneurs could with relative ease mask their actual country. As such we could test (for example, by examining creators' social media accounts) whether projects from countries other than the US attempt to disguise their country to increase the probability of crowdfunding success, as suggested by this project. This 'disguised country' sample could be then tested to determine how it affects their probability of success relative to projects from the US and elsewhere that truthfully report their countries. This direction, while difficult to implement, is promising as it tackles the broader issue of unregulated markets and disclosure.

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