*A Simple Crowdfunding Model**

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April 1, 2017

Abstract

Inspired by the newly emerging trend that traditional reward crowdfunding platforms start to partner with equity crowdfunding platforms, I set up a theoretical model using threshold mechanism to study the implications of such combinations. The model, which uses a simple binary-funder-type and β-distribution based valuation system, is able to make several interesting predictions. (1) The creator's credit constraint will always be satisfied, and the creator can reap all the ex-ante expected social surplus, reaching a socially optimal result. (2) The platform offers lower cost of capital and a demand signal. (3) A higher investment cost motivates the creator to condition her investment choice on a successful observation of her ex-ante expected demand signal. (4) The creator weights the value from an additional bid against the equity cost of acquiring it when setting up the optimal threshold. (5) An objectively promising project implies different results than a subjectively promising one. The creator is likely to set herself up for failure in the latter case. (6) How the creator gives back the promised equity does not affect the creator's ex-ante optimal choices or her ex-ante expected utility.

*I thank Professor David Miller for his invaluable guidance and instructions. I also thank Xiang Meng for her suggestions and help.

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1 Introduction

At the age of seven when I first learned how big the size of the earth population was, I had this crazy idea about becoming a millionaire, or even a billionaire, by simply collecting one penny from everyone else. Unfortunately, I have not yet succeeded carrying out that plan to this day. One main reason is the realization that I figured as I grew older — regardless of how small the amount is or how rich they are, people do not like spending their money for nothing. This recognition, far from discouraging me from holding onto my childhood fantasy, constantly inspires me to understand and explore the potential power of a huge crowd.

As an ardent Esports follower, I have witnessed my childhood fantasy coming true for the past few years. Using crowdfunding based on its huge player base, Valve Corporation has held several record-breaking gaming tournaments in the history of Esports for the last five years. For example, starting from a base prize pool of 1.6 million dollars, the yearly biggest tournament of the competitive game Dota 2 ended up with a final prize pool containing more than 20 million dollars in the year of 2016[1]. In fact, the use of crowdfunding is not born in modern times. Back in the year of 1783, Mozart offered his manuscripts to whoever financially backed him for a piano performance in a Viennese concert hall. Other famous examples include the building of the Statue of Liberty and the Pebble Watch.

Alegre, I., & Moleskis, M. (2016) defined the concept of crowdfunding as ”an alternative model for project financing, whereby a large and dispersed audience participants through relatively small financial contributions, in a purposeful project, in exchange for physical, financial or social rewards. It is usually done via Internet-based platforms that act as a bridge between the crowd and the projects.” Based on this definition, a typical crowdfunding project involves three major components. Conforming to the names used by Agrawal, Catalini, and Goldfarb (2014), I label the projects' initiators as **creators** and the projects' supporters as **funders**. The last major component is the crowdfunding **platform**. With the help of the internet, almost all the crowdfunding activities nowadays are performed on online platforms.

[1]For more information, one can visit the site http://dota2.prizetrac.kr/

Appendix A contains a short list of the leading crowdfunding platforms in North America and Europe.

Following the terminology used in the literature, I divided the funding strategies adopted by the platform into four categories: reward, equity, donation, and debt. Reward crowdfunding can be best understood as the case where funders financially support the creator in exchange for the product, or more generally, the reward promised by the creator. On an equity crowdfunding platform, the funders act like venture capitalists except they only put in a small amount of money and expect to receive some equity shares from the creator if the project gets initialized. Donation-based crowdfunding platform is self-explanatory, where the funders support the project without any expectation of receiving anything in return. Lastly, debt-based crowdfunding platform emerges only recently, where the funder essentially performs as a tiny bank, from which the creator can take small loans if the creator successfully persuades the funders to support her project. Compared to an equity crowdfunding, the creators only need to pay back the funders based on a pre-determined interest rate. Intuitively, one may think the debt-based crowdfunding platform gives more incentive for the creators to participate, whereas the equity-based crowdfunding offers more motivations for the funders to be involved.

The third column in the table in Appendix A specifies the initialization rule applied by the platforms. A fixed funding initialization rule implies the creator can only initialize her project if the accumulated capitals she is able to raise surpass her pre-determined threshold. A flexible funding initialization rule indicates that the creator receives whatever amount she is able to raise during the lifetime of her post and then determines whether to carry out the project. Intuitively, a flexible funding initialization rule is more susceptible to moral hazard threat, though such threat is always present under a crowdfunding scheme.

Moritz, A., & Block, J. H. (2016). and Alegre, I., & Moleskis, M. (2016) provided excellent surveys on the current stage of research in this nascent crowdfunding field. Inspired by the trend that a lot of reward-based crowdfunding platforms have started a partnership with equity-based crowdfunding platforms, and by my reading that few researchers have touched upon this newly emerging movement, this paper attempts to build up a simple theoretical model to understand the implications behind such combinations. The simple model adopted features from Strauzs (2016) model, whereby he studied the issue of moral hazard in reward crowdfunding, and extended based on his model by assuming the creators are unable to reach to the entire market at the beginning of her project due to the credit constraint.

The structure of this thesis is as follows. Section 2 sets up the model based on the three major components under a crowdfunding scheme. In Section 3, I attempt to understand the predictions from the model by examining the results from a specific numerical example. Section 4 discusses potential extensions of the model that can be used to study issues such as moral hazard, asymmetric information, and motivations, etc. Limitations of the model are also briefly discussed in Section 4. Section 5 concludes.

2 The Simple Model

2.1 The Funders

Following Strausz (2016) binary-type-consumer model, I consider two types of funders: funder i who values the product, $v_i = 1$, or not, $v_i = 0$. I refer in the following texts funders with valuation 1 as type-1 funders and valuation 0 as type-0. Furthermore, I assume the crowd is uncoordinated, and funder forms her valuation based solely on the product produced by the creator. In particular, I consider funders' valuations to be i.i.d. with $Pr\{v = 1\} = p$ and $Pr\{v = 0\} = 1 - p$, where $p \sim beta(a, b)$ is commonly held among all funders. Using β-distribution to model funders' valuations has several major advantages compared to other probability distributions. For example, the Bayesian updating rule for β-distribution is straightforward. A proof can be found in Navarro and Perfors (2005). It works as follows: starting with common prior $beta(a, b)$, after receiving k successes in n trials, the posterior belief becomes $beta(a + k, b + n - k)$. Another advantage is that I could use BetaBinomialDistribution to model the number of type-1 funders in the population. A brief discussion of this distribution can also be found in Navarro and Perfors (2005).

To further simplify the analysis, I separate the crowd of funders into two distinct populations. Specifically, I denote n as the total number of funders who do not surf on the crowdfunding platform and n_1 as the number of type-1 funders in this population. In other words, funders in this population are effectively consumers who do not perform any "funding" behaviors and do not have any information about the product until the creator is able to initialize her project by garnering enough early capitals from the crowdfunding platform. Equivalently, the creator will never reach this population of funders if she fails to initialize her project. The rest of the funders in the crowd is denoted by m, who are regular visitors to the crowdfunding platform, and m_1 denotes the number of type-1 funders in this population. Unlike the funders in the other population, funders in the crowdfunding population can decide whether or not to fund the creator based on their valuation of the product and corresponding updated belief of the probability p, which I will study in Section 4. Lastly, as a note, I define the funder's utility to equal her total returns derived from interacting with the creators.

2.2 The Creators

In one of the fundamental papers about crowdfunding, Agrawal, Catalini, and Goldfarb (2014) outlined two major incentives for creators to use crowdfunding for raising early capitals: 1). lower cost of capital, and 2). accessibility to more information. In the simple model, I include the third incentive for creators by assuming they are credit-constrained: 3). to initialize the project. The credit-constraint assumption stipulates that even in the best case scenario, where all m funders in the crowdfunding population are type-1, the creator is still unable to fund her project if every funder only contributes her valuation, i.e. $m * 1 < I$, where I denotes the entry cost. Therefore, the creator needs to set up a bid $x > 1$ on the platform to overcome this constraint. And to compensate to the funders who are willing to bid more than their valuations for the product, the creator will return an α share of the profits she will earn from the non-crowdfunding population if the project gets initialized. In particular, α is set to be a fixed proportion of the profits the creator commits to returning to each bidding funder. It follows naturally that the initialization of a project requires $x * T \geq I$, where T is the number of bidders needed in the crowdfunding population and x is the bid. Once the project is initialized, I impose that the creator commits to carry out the plan and is able to reach the whole non-crowdfunding population wherein she can maximize accordingly. In addition, I also assume that the creator has no other funding options besides the crowdfunding platform. Lastly, without loss of generality, I assume the marginal cost of production equals 0 for the creator.

2.3 The Platform

Based on the aforementioned characteristics of the creators and funders, the crowdfunding platform I am proposing combines both reward crowdfunding and equity crowdfunding. On the platform, the funder can receive both the product and future monetary returns if she is willing to fund the creator x. The creator sets up T, α, and x to overcome her credit constraint and to initialize the project. In particular, the platform adopts a simple threshold mechanism where the creator wants to maximize her ex-ante expected profits, and the funder decides whether to bid based on the threshold T the creator sets, the equity share α the creator commits to returning, the bid $x > 1$ the creator proposes, and her updated belief about others' preferences.

2.4 Objective and Constraints

In the simple model, the creator's objective is to maximize her ex-ante expected utility subject to various constraints. But first of all, let me assume the creator is just like all the funders regarding the potential success of the project: the creator shares the funders' common prior belief about p. Moreover, apart from the credit constraint, which stipulates $x * T \geq I$, I also require incentive compatibility and individual rationality. Let $u_i(\cdot)$ denote the utility type-i funder derives by bidding to the project. Specifically, incentive compatibility indicates $E[u_0(0)] = 0$ and $E[u_1(x)] \geq 0$, and individual rationality demands $E[u_1(x)] \geq E[u_1(0)]$ and $E[u_0(0)] \geq E[u_0(x)]$. I can combine the two constraints into a more compact form:

$$E[u_1(x)] \geq E[u_1(0)] = 0 = E[u_0(0)] \geq E[u_0(x)]$$

The objective function for the creator is

$$\arg\max_{\alpha,T,x} E[\pi] = Pr(m_1 \geq T) \cdot E[\underbrace{(xm_1 - I)}_{①} + \underbrace{(1 - \alpha * m_1)(pn \cdot 1)}_{②} |m_1 \geq T] \tag{1}$$

where ① is the profits from the bidding funders in the crowdfunding population and ② is the profits from the non-crowdfunding population after paying back the bidding funders' equity earnings. Similarly, I can write the expected utility for type-i funder as:

$$E[u_i(x)|v_i] = Pr(m_1 \geq T - 1|v_i) \cdot E[u_i|v_i \cap m_1 \geq T - 1] \tag{2}$$

$$E[u_i(0)|v_i] = 0, \text{ for } i = 0,1 \tag{3}$$

where the $T-1$ term in equation (2) is resulted from funder i being the bidder, and equation (3) holds directly from incentive compatibility and individual rationality constraints.

Expanding the utility functions and maximizing the objective function involve proper updating of beliefs from all crowdfunding participants. I will illustrate this point through a simple numerical example discussed in the following section.

3 A Simple Numerical Example and Results

3.1 Model Parameterization and Solution Concept

Imagine a simple world with $n = 200$ and $m = 16$. And the creator shares the common prior that $p \sim F = \beta(1, 1)$ with all the funders and faces $I = 20$. Starting from the crowdfunding funder's perspective, upon forming her valuation of the product, the funder correspondingly updates her belief of p either to $F^+ = beta(2, 1)$ if she is type-1 or to $F^- = beta(1, 2)$ if type-0. When calculating the expected ex-ante utilities for all crowdfunding participants, as in Section 3, the equations depend on the realized number of type-1 funders in the crowdfunding population. In particular, the project will not be initialized if $m < T$. Therefore, conditioning on the project being initialized, i.e. $m_1 \geq T$, all funders as well as the creator update their beliefs once again:

Using BetaBin(·,·,·) to denote the BetaBinomial Distribution, I get:

$$\text{Creator: } \begin{cases} PDF(p|m_1 \geq T) = \frac{PDF(p) \cdot Pr(m_1 \geq T|p)}{Pr(m_1 \geq T)} & \text{Posterior PDF for } p \\ (F, Bin(m, p), BetaBin(1, 1, m)) & \text{Distributions of } (p, m_1|p, m_1) \end{cases} \tag{4}$$

$$\text{Type-1 funder: } \begin{cases} PDF(p|m_1 \geq T) = \frac{PDF(p) \cdot Pr(m_1 \geq T-1|p)}{Pr(m_1 \geq T-1)} & \text{Posterior PDF for } p \\ (F^+, Bin(m-1, p), BetaBin(2, 1, m-1)) & \text{Distributions of } (p, m_1|p, m_1) \end{cases} \tag{5}$$

$$\text{Type-0 funder: } \begin{cases} PDF(p|m_1 \geq T) = \frac{PDF(p) \cdot Pr(m_1 \geq T|p)}{Pr(m_1 \geq T)} & \text{Posterior PDF for } p \\ (F^-, Bin(m-1, p), BetaBin(1, 2, m-1)) & \text{Distributions of } (p, m_1|p, m_1) \end{cases} \tag{6}$$

Since type-1 funder knows her own valuation, from her perspective, the project only needs at least $T - 1$ more type-1 funders to initialize. The similar rationale applies to the $m - 1$ term shown up in the above belief system. Moreover, when calculating the probability term, I have to use the correct funder-type-specific distribution for m_1. Based on this belief system, I can calculate each type of funder's ex-ante expected payoff:

$$E[u_1(x)] = Pr(m_1 < T-1) \cdot 0 + Pr(m_1 \geq T-1) \cdot E[u_1 | m_1 \geq T-1] \tag{7}$$

$$= Pr(m_1 \geq T-1) \cdot (\underbrace{(1-x)}_{③} + \underbrace{(\alpha * n * E(p|p \sim \text{PosteriorP in Eq(5)})}_{④}) \tag{8}$$

where ③ indicates the disutility type-1 funder gets by bidding more than her valuation, and ④ gives the expected equity return from the creator. Similarly, for type-0 funder:

$$E[u_0(x)] = Pr(m_1 < T-1) \cdot 0 + Pr(m_1 \geq T-1) \cdot E[u_0 | m_1 \geq T-1] \tag{9}$$

$$= Pr(m_1 \geq T-1) \cdot ((0-x) + (\alpha * n * E(p|p \sim \text{PosteriorP in Eq(6)})) \tag{10}$$

When maximizing the objective function (1) subject to the constraints outlined in equations (2) and (3), I consider one specific class of strategies for the creator. In particular, I imagine that the creator is concerned with the possibility of raising enough early capitals and therefore is unwilling to overshoot the minimum target level, I. In other words, she will pick x and T ex-ante such that $x \cdot T = I$, which effectively reduces the set of choice variables for the creator to only α and x (or T). Since $T \in [1, m]$, I could simply conduct a grid search for every possible value of T and find the optimal set of maximizers for the creator.

3.2 Results and Interpretation

In Table 1, I presented the set of maximizers given every value of T and the pre-specified parameter values. Table 2 shows the sets of maximizers if I double the size of n, holding everything else constant. Table 3 contains the sets of maximizers if I instead increase the value of I, holding everything else constant. Based on Table 3, one observation is that as T grows relatively larger than the size of the crowdfunding population, m, the optimal threshold T for the creator becomes an interior point rather than a boundary point, i.e., $T = 6$ instead of 1. Table 4 with an even larger I-m ratio illustrates this point more clearly. Table 5 displays the set of maximizers when I increase the size of the crowdfunding population m such that the creator will no longer face a credit constraint, holding everything else constant.

Let us first look at Table 1 and keep the original model parameterization in mind. It is immediately evident that in this class of strategies, the creator will be best off ex-ante if she sets $T = 1, x = 20, \alpha = 14.25\%$. In other words, the creator will get the maximum ex-ante expected payoff if she simply sets the bid to be equal to the entry cost, I, and only seeks one bidder from the crowdfunding population. To obtain such a high bid, the creator is willing to return 14.25% of the profits she earns from the non-crowdfunding population to the bidder. One should be aware that α here is not chosen randomly but specifically to favor the creator in the sense that she gets all the ex-ante expected social surplus from this threshold mechanism. To see this point, one needs to make several observations.

Firstly, by conducting a grid search based on T's value, I effectively reduce the set of choice variables for the creator to only α. When maximizing her objective function, the creator only needs to choose the optimal α given T and x. The construction of the optimization problem implies that the creator has perfect information regarding the funders' utility functions. Since the creator could adjust any α that gives type-1 funder positive utility in expectation for any given T and x when optimizing, the creator's optimal α should always make the individual rationality constraint for type-1 funder bind. In other words, type-1 funder's ex-ante expected utility should always be 0. With type-1 funder getting 0 ex-ante, type-0 funder will receive negative ex-ante expected payoff if she bids x because she not only values the product less but also is more pessimistic regarding others' preferences of the product compared to the type-1 funder. The individual rationality constraint for type-0 funder only binds when the creator expects no type-0 funder in the crowdfunding population, i.e. $T = m$.

Additionally, based on the objective function, the creator loses nothing even if the project fails to initialize ex-post. This may help explain why the creator is willing to set such a high bid x in the model intuitively. On the contrary, if the ex-post number of type-1 funders from the crowdfunding population exceeds T, the creator receives more funding than she needs. Since the extra funding does not come from the non-crowdfunding population, the creator does not need to return this part of endowment and could keep them for herself, unless the total equity share held by all bidders, $m_1 * \alpha$, exceed 1. Though the overall effect on the creator's ex-post utility is arbitrary because more bidders take away more of the creator's profits from the non-crowdfunding population, the ex-post arbitrariness is of less concern here because I am interested in how the creator maximizes her utility ex-ante.

Once the project gets initialized, by setting the market price to be 1, the creator reaps all the funders' consumer surplus as every type-1 funder in the non-crowdfunding population will buy the product. Moreover, by maximizing the objective function using the aforementioned set of maximizers, the creator gets all the surplus from this mechanism, and the outcome is socially optimal. The creator would not have been able to achieve this socially optimal outcome due to the credit constraint were there no such crowdfunding platform. Though I limited the outside funding options for the creator by assumption, one could still ask what will happen if I instead relax this assumption to include funding from a venture capitalist. The short answer here is that the crowdfunding mechanism should still be weakly preferred.

As predicted by the model, under the original model parameterization, the creator is best off if she is only looking for one bidder, which sounds very much like the creator is seeking a venture capitalist except that this venture capitalist has no bargaining power. In other words, the bidder, or the "venture capitalist," that the creator seeks is expected to accept any x and α, including those that essentially give him 0 ex-ante expected utility. In a real life setting, one can easily imagine that almost no venture capitalist will take such a deal. Instead, it is highly likely that the creator needs to agree on a larger α than the one from the crowdfunding platform in exchange for the funding, resulting in less ex-ante expected utility for the creator and thus rendering the crowdfunding platform preferable. Therefore, the crowdfunding platform offers a way for the creator to obtain early capitals at a lower cost.

That the bidder is receiving 0 ex-ante expected utility may then raise the question why anyone would accept the deal. One could understand this in two ways. Firstly, unlike the venture capitalist, the funder does not have any bargaining power when deciding whether to bid. All a funder has is a take-it-or-leave-it deal given by the crowdfunding platform. Since the type-1 funder will be indifferent between bidding and not bidding because of her 0 ex-ante expected utility, I could specify the strategy for the type-1 funders to always bid in such cases. Alternatively, the creator could leave the type-1 funder ϵ amount of ex-ante expected utility by adjusting the value of α, which guarantees the bid from type-1 funders. In summary, one could see that $T = 1$ being the optimal choice in this case does not imply that the creator is looking for a venture capitalist, but rather is a result of the relationship among I, m, and n, which will be discussed in Section 4.

Though I approached the maximization problem by conducting a grid search for the values of T, I have not yet discussed the interpretations of these values. By setting the threshold T to be a specific number, the creator is only willing to carry out the project if there turns out to be more than T number of bidders in the crowdfunding sample. Essentially, the creator is conditioning her investment choice on the demand signal she learns from the crowdfunding population. Moreover, by assumption, she is committed to carrying out the project once the threshold T is surpassed. Therefore, she wants to set the T optimally such that it maximizes her ex-ante expected utility from the crowdfunding mechanism. Under the initial model parameterization, the optimal value for T is 1, indicating that the creator uses the crowdfunding platform more about raising early capitals than learning the potential demand for her product. This, as one will see soon, is not always the case.

Lastly, if one ignores the optimal choice of T in Table 1 and looks at the whole table, it is not hard to observe that the project is always profitable ex-ante for the creator for any T. Such profitability feature implies that the creator will always want to enter the market if she faces no credit constraints, which also helps explain why the creator cares less about the signal she learns from the crowdfunding platform. In real life, one can expect most of such projects to be picked up by venture capitalists because of their profitability. But as I discussed above, the creator may be better off if she opts for the crowdfunding platform by retaining as much ex-ante expected utility as possible.

Moving on to Table 2, where I get the results, *ceteris paribus*, by doubling the size of the non-crowdfunding population, one observation is that the values of both the creator's ex-ante expected utility and α have changed compared to the ones in Table 1. One can easily predict such changes by the construction of the model. Based on the discussion above, the creator chooses the optimal α such that all type-1 funders in the crowdfunding population will have 0 ex-ante expected utility. Hence, by equation (8), with n doubled, the value of optimal α for each T has to be half of the value in the original model parameterization, whereby the ex-ante expected utility of type-1 funder can be kept to be 0. Similarly, one can predict the change in the creator's ex-ante expected utility. Going back to equation (1), I could rewrite it as:

$$\arg\max_{\alpha,T,x} E[\pi] = Pr(m_1 \geq T) \cdot E[\underbrace{m_1(x-\alpha pn)}_{⑤} + \underbrace{pn - I}_{⑥} | m_1 \geq T] \tag{11}$$

As discussed above, the optimal value of α is halved compared to what it is under the original model, and with n doubled, the expression of ⑤ remains unchanged, but there will be an extra pn from ⑥. So with the modification, the change of the creator's ex-ante expected payoff is $Pr(m_1 \geq T) \cdot E[p|p \sim \text{PosteriorP in Eq(4)}]n$. In general, if I scale the non-crowdfunding population size n by a factor c, the optimal values of α will be $\frac{1}{c}$ of the ones in the original model, and the creator's ex-ante expected utility will change by $Pr(m_1 \geq T) \cdot (c-1)E[p|p \sim \text{PosteriorP in Eq(4)}]n$.

This modification implies that as the non-crowdfunding population size becomes larger, holding everything else constant, the profitability of the project grows accordingly. One way to interpret n is to treat it as an indicator of how promising objectively the project is. The rationale behind this interpretation is that without the credit constraint, a very promising project will be favored by a larger crowd, corresponding to a larger n value. Intuitively, the more promising a project is, the higher the ex-ante expected payoff for the creator will be, which is exactly what the model predicts. Moreover, because of the project's high potential for profitability, the creator does not need to offer a large equity share, α, in exchange for the early funding, which is captured by the smaller α values in Table 2.

So far, I in the model only denotes the entry cost. However, since the creator also devotes time and efforts to the project during the preparation process, this preliminary cost structure may not be sufficient. Therefore, one rationale behind having a larger I is to consider that the creator will internalize the preparation cost while looking for funding in order to compensate for her own efforts. Such internalization should then correspond to the increased value of I as I now represents the total investment cost. Table 3 and 4 examine such cases while holding everything else constant.

As mentioned previously, as I grows relatively larger compared to m, the optimal T starts deviating from the lower boundary 1. Such deviations are evident in both Table 3 and 4. The important takeaway here is that signaling effect matters, even in the case where the project is always profitable ex-ante as in Table 3. With $I = 80$, the creator commits to carrying out the project only if there is at least a reasonable amount of type-1 funders in the crowdfunding population, which in this case is 6. Moreover, though setting any other T also results in positive ex-ante expected payoff, $T = 6$ maximizes it. As discussed before, because the creator is unable to react ex-post due to commitment, it is crucial and necessary for her to choose optimally ex-ante. With $I = 150$ as in Table 4, the creator is only willing to commit to the project if there are at least 12 type-1 funders in the crowdfunding population. More importantly, when the total investment cost I is a lot larger compared to the size of the crowdfunding population, one begins to see negative ex-ante expected payoff from some threshold choices T. For example, if the creator sets $T = 1$ as in the original model, she has to return 111.75% of the future profits to compensate the bidder for the large bid x and only to make the bidder indifferent, resulting in negative ex-ante expected payoff. In results not shown here, with $I = 200$, the optimal threshold T becomes 16, corresponding to the only positive ex-ante expected payoff for the creator, which is less than 1. In comparison to the results of the original model with low I, one can observe that as I grows larger, the creator starts to care more about learning the market demand for her product from the signal sent by the crowdfunding population. The credit-constraint becomes less of a concern because it can always be satisfied through the crowdfunding platform. But as one can observe from Table 4, some sets of parameter choices do not generate positive ex-ante expected payoff for the creator. In the original model, however, it is hard to argue the importance of the signaling effect because the optimal T equals to 1 due to the small investment cost I.

From another point of view, the creator knows ex-ante that the project is unlikely to be profitable due to the large investment cost I and relatively small crowd $m+n = 216$. Suppose there were no credit constraint, it would still have required at least 150 type-1 funders from the non-crowdfunding population to cover the total investment cost I, which is unlikely to happen given the creator's belief. Therefore, she only wants to commit to the project if she observes a promising signal from the crowdfunding population. In other words, the creator first forms her ex-ante expected market demand that will render the project profitable and then conditions her investment decision upon receiving such signal from the crowdfunding platform.

Previously, I interpret n as the objective promisingness of the project. Similarly, m can be understood as the popularity of the crowdfunding platform. The rationale is simple. If a crowdfunding platform is popular, one should expect more regular visitors on this site. Table 5 shows the results when I only increase m. The modified value of $m = 25$ implies the possibility that the creator no longer faces a credit constraint. Indeed, by having $m > T$, I observe the kink where a reward- and equity-based crowdfunding transitions into a reward crowdfunding. In particular, by setting $T = 20$, the creator's best choice is to treat the funders in the crowdfunding pool as the funders in the non-crowdfunding pool by setting $x = v_1$ and $\alpha = 0$. The interesting point here is that doing so does not generate the best ex-ante expected payoff for the creator. Since the creator could use the equity share α given by the crowdfunding mechanism to extract more fundings from type-1 funders in the crowdfunding population, it is to the creator's interest to set lower T to utilize the equity feature and to maximize her ex-ante expected payoff. Indeed, as one can see from Table 5, the optimal set of maximizers is $T = 2, x = 10, \alpha = 6.7315$.

A very important implication of setting a low threshold T that I have not yet discussed is that it implies a very high bid x. This relationship is caused by the specific class of strategies I am working with, where I imposed $T * x = I$. As discussed before, the credit constraint can always be satisfied by having a specific set of maximizers for a given T. And the number of bidders in the crowdfunding population will be the number of type-1 funders, whose bidding decisions depend on x and α but valuations do not. Since for a given T, the set of maximizers x and α always induces all type-1 funders to bid, therefore, as long as ex-ante an extra bid gives more payoff than the expected equity cost, the creator has an incentive to set T low. This argument perhaps is more rigorous compared to the raising-capital argument I discussed earlier when justifying the optimal choice of $T = 1$ under the original model parameterization. But as one can see from Table 4, where the equity cost gives more disutility than the utility given by the high bid ex-ante, choosing a larger T that makes the high-equity-cost effect dissipate is more preferable. In Table 5, with low investment cost, a low threshold T implies a high bid x and a small equity share α, which, by the above argument, should be preferred by the creator. Indeed, $T = 2$ offers the highest ex-ante expected payoff for the creator, and the ex-ante expected payoffs given by other low thresholds T do not differ much from the optimal value.

What role does m play here? Firstly, having a larger m means that the creator can expect more type-1 funders from the crowdfunding population. Therefore, as long as the above argument holds, the creator should expect a higher ex-ante payoff from a more popular platform for the same level of threshold because of the potential for more bidders. Indeed, by comparing the results from Table 1 and 5, I find that the creator gets more ex-ante expected payoffs for all $T \in [1, 16]$. Secondly, a more popular platform implies that the creator can expect more accurate demand signal from the crowdfunding population. Suppose in an extreme case, the size of the crowdfunding population is 2. Upon observing one bidder from the crowdfunding population, the creator should not be confident to expect half of the non-crowdfunding population to be type-1 funders because of the small sample size. Thirdly, all the funders in a popular crowdfunding population incorporate the results that the creator is able to expect more bidders and receive more accurate demand information into their utility functions, and therefore should demand higher equity shares α for revealing their private information. The model indeed predicts such behaviors by higher α values in Table 5. Lastly, the value of m also affects the optimal choice of T, as one already sees in Table 5. A suggested approximate formula will be discussed in more detail in Section 4.

3.3 Summary of Results

By examining the original model parameterization and comparing the original results with other results given by different modified model parameterizations, the model makes several interesting predictions. (1). The credit constraint can always be satisfied via the equity and reward crowdfunding platform. (2). The platform offers lower cost of capital. (3) The socially optimal outcome can be achieved by the platform and the creator receives all the expected social surplus ex-ante. (4) With an objectively promising project, the creator is able to raise funding with a small equity share. (5) With a higher investment cost by which the project may not always be profitable ex-ante, the creator conditions her investment decision on successful observation of the expected demand signal from the crowdfunding platform. (6) A popular platform offers more accurate demand signal. (7) The creator expects higher ex-ante expected utility from a more objectively promising project and a more popular platform. (8) When facing a highly profitable project implied by a low I-n ratio, the creator cares less about learning the demand and thus setting a low threshold for initializing the project. (9) When setting the optimal threshold, the creator weights an additional bid against the equity cost of acquiring it.

In the next section, I will revisit some of the results discussed here and look at some other potential extensions and limitations of the model.

4 Extensions and Limitations

4.1 Cost Structure

In the discussion of the results from the original model parameterization, I mentioned that the creator loses nothing even if the project fails to initialize. One can also see this feature from the objective function (1) by observing that the objective function implicitly specifies the utility to be 0 whenever $m_1 < T$. This, however, could not be possibly true in real life. The creator's internalization of her preparation cost into a higher I also does not solve this problem, because the higher I only factors into the creator's utility function whenever the project could be initialized given specific T. One simple modification would be adding a "frustration cost", F, into the objective function. This cost is only present when the project fails to initialize, whereby the creator gets frustrated by her fruitless efforts. I can thus rewrite the objective function as:

$$\arg\max_{\alpha,T,x} E[\pi] = -F \cdot Pr(m_1 < T) + Pr(m_1 \geq T) \cdot E[(xm_1 - I) + (1 - \alpha * m_1)(pn \cdot 1)|m_1 \geq T] \tag{12}$$

For illustration purpose, I set $F = I$ using the original model parameterization and Table 6 shows the result. The immediate observation is that the frustration cost has little effect on the expected utility for T small, but large negative effects for T large. Because the realization of the number of type-1 funders in the crowdfunding population is totally independent of x, α, and T, the larger the threshold T is, the less likely the ex-post realization will surpass it and therefore the more likely the creator incurs the frustration cost. In this way, I could interpret F also as the cost for expecting high signals from the crowdfunding population, reflecting the saying that 'the higher the expectations, the greater the disappointment.' In results not shown, using $F = 30$ and under Table 4's model parameterization, the addition renders the project totally unprofitable. Because it is somewhat arbitrary what the right number of F should be, this modification was not included in the original model.

4.2 Change of the α Definition

In the original model, I defined α to be a fixed proportion of future profits the creator commits to returning to each bidding funder. Alternatively, I can define α to be a fixed proportion of future profits that will be shared by all bidding funders. By this definition, the objective function (1) and funders' utility functions (7) and (9) will become:

$$\arg\max_{\alpha,T,x} E[\pi] = Pr(m_1 \geq T) \cdot E[(xm_1 - I) + (1-\alpha)(pn \cdot 1)|m_1 \geq T] \tag{13}$$

$$E[u_1(x)] = Pr(m_1 \geq T-1) \cdot E[(1 - x + pn * \frac{\alpha}{m_1 + 1})|m_1 \geq T-1] \tag{14}$$

$$E[u_0(x)] = Pr(m_1 \geq T-1) \cdot E[(0 - x + pn * \frac{\alpha}{m_1 + 1})|m_1 \geq T-1] \tag{15}$$

where as with equation (8) and (10), despite equation (14) and (15) look alike, the random variables m_1 and p follow the funder-type-specific distributions.

Results are shown in Table 7 using the alternative definition of α. It should not be surprising that both α definitions give the same ex-ante expected payoff for the creator. After all, the creator maximizes her ex-ante expected utility by extracting all the funders' information rent from the crowdfunding population as well as all the consumer surplus from the non-crowdfunding population. Therefore, regardless of how she hands back the equity share to the bidders, the optimal ex-ante expected payoff should not be changed (within the specific class of strategies considered here). Because the original version of α makes the interpretation of results more intuitive and can be computed more efficiently, it is adopted in the model.

4.3 Choice of Optimal T

Based on the discussion in Section 3, if a project is objectively promising and is launched on a popular crowdfunding platform, the creator will set a low threshold T for initializing the project facing a low investment cost I. It turns out that one could approximately calculate the optimal threshold T by the following formula:

$$T^* \approx m \cdot \frac{I}{m+n} \tag{16}$$

Since m is relatively small in the original model, therefore I concluded at the end of Section 3 that a low I-n ratio implies high profitability. A more precise, yet still approximate, statement should be a low I–$(n+m)$ ratio implies high profitability. One way to understand this approximation is that the creator forms her ex-ante expected demand signal based on the entire crowd with size $m+n$ as if there were no credit constraint. This formula makes it easy and convenient to understand the relative importance between the signaling effect and the funding opportunity offered by the crowdfunding platform based on different parameter constellations. Since the model can be completely represented by closed forms, an exact formula could be derived, but the implication should not differ significantly.

4.4 Optimism and Pessimism

Another advantage of using β-distribution to model the belief system is that it enables one to model the confidence level of the participants in the model. For example, a prior belief of $\beta(10,1)$ implies the agent is extremely optimistic regarding the project's potential success, and similarly $\beta(1,10)$ indicates pessimistic attitudes. Moreover, a prior belief of $\beta(10,10)$ is different from a prior belief of $\beta(1,1)$ in the sense that the participant with a prior belief of $\beta(10,10)$ would not alter her expectation of others' preferences upon observing her own type as much as she would with a prior belief of $\beta(1,1)$. In general, the larger the value of a and b, the more persistent the prior belief will be after the funder forms her own valuation.

For illustration purposes, Table 8 shows the results when I change the common prior to be $\beta(10, 10)$. It is immediately evident that the ex-ante expected creator payoff for any T is extremely close to the others. This observation is a result of the persistence of the funders' prior beliefs given large a and b. As a result, after forming their own valuations, both type-1 funders and type-0 funders only slightly adjust their expectation of others' preferences. The slightly larger α values compared to those in Table 1 are resulted from the lower degree of optimism from type-1 funders with the prior belief of $\beta(10, 10)$, whereby the creator has to agree on more generous terms in exchange for the bids. The original model uses $\beta(1, 1)$ as the common prior because the uniform distribution is hugely preferred in modeling and makes the results more interesting.

Another modification using the β-distribution is to model asymmetric beliefs between the creator and the funders. In the original model, I assumed that the creator shares the funders' common prior belief; however, in real life, it is more likely that the creator is more confident and optimistic than her targeted population regarding the potential success of her project. In contrast to n denoting the project being objectively promising, I define the project to be subjectively promising whenever the creator has a prior belief $\beta(a, b)$ with $a > b$.

For illustration purposes, Table 9 contains the results when the creator holds a prior belief $\beta(5, 1)$. Comparing with the results using the original model parameterization, one can observe that all the ex-ante expected creator payoff go up except for the case where $T = 1$. The change also alters the optimal choice of T. Such changes match the real world in the sense that one would expect an optimistic creator to be fairly confident in her project, which can be reflected by her expecting higher ex-ante payoffs. But such optimism may lead to failed initialization if the actual funders do not hold similar views towards the project. This potential pitfall is captured by the model. Having the optimal $T = 7$ in this case, the creator's objective optimism induces her to believe that it is highly possible that there will be seven type-1 funders in the crowdfunding population, which will likely not match the reality and abort the profitable project.

4.5 Relaxation of Commitment Constraint

One important constraint I set up for the creator in the model is the commitment constraint. In particular, I do not allow the creators to react ex-post after she learns the signal from the crowdfunding population. It is likely that the ex-ante choice of T is not optimal based on the demand signal the creator learns ex-post, especially in the case where the creator is over-optimistic. By relaxing the commitment constraint and allowing the creator to react ex-post, I need to worry about the potential issue with moral hazard. If a threshold is surpassed and the creator is able to overcome the credit constraint but learns a poor demand signal from the crowdfunding population, she may abort the project and take the money away. As mentioned in Section 2, Strausz (2016) studies this issue in depth using mechanism design approach. For now, this relaxation is reserved for future research.

Apart from the threat of moral hazard, relaxing the commitment constraint makes the model match more closely to the real world, where one observes many creators use crowdfunding platforms not primarily for raising capitals. Being able to react ex-post, the creators can adjust their investment decision, products features, and even financing strategies based on the feedback they get from the early adopters in the crowdfunding population. Since such adjustments are hard to model and often happen on a case by case basis, empirical studies are more fitting for research in this area.

4.6 Robustness and Weird Cases

Agrawal, Catalini, and Goldfarb (2014) made an observation in their paper that funding from the creator's friends and family plays a key role in the creator's capital raising campaign. Suppose these people support the creator via the crowdfunding platform, then the i.i.d. assumption and the construction of funders' valuations will be violated, because being a member of the creator's family or the creator's friend will immediately imply the funder is a bidder regardless of her actual valuation. This violation will in turn render the demand signal from the crowdfunding platform noisy and inaccurate. Fortunately, the model can withstand such cases by decreasing I by an amount that is equivalent to the early funding the creator receives from her friends and family.

Weird results may arise when I consider asymptotic cases. For example, the model breaks down when I allow n to go to infinity because the crowdfunding mechanism will no longer be able to restrict the type-0 funders from bidding because of the infinite ex-ante expected payoff from the infinite non-crowdfunding population. The creator thus cannot learn any meaningful demand signal which she does not need because the project is guaranteed to be profitable by the infinite degree of objective promisingness. Another case I can consider is when m goes to infinity. Based on the discussion in Section 3, the creator will no longer face the credit constraint but always have to commit to the project because the threshold T will always be surpassed for finite T.

4.7 Other Extensions and Limitations

One major limitation in the results is how I solve for the maximizers. Though I made the calculation of the maximizers much more tractable by considering the creator to be precautionary and thus unwilling to overshoot the target, it is not clear at all whether such approaches indeed give the optimal set of maximizers when I allow $x * T > I$. A preliminary examination shows that whenever $m < I$, the approach indeed offers the optimal set of maximizers. When $m > I$, the weird bid value x I found in Table 5's last 5 columns will be gone. The optimal bid will instead be 1. The implication from the preliminary check is that setting x according to $x * T = I$, which is the "safest" strategy for the creator, is always better than trying to overshoot the desired target. This feature of the model, if it is indeed true, protects the funders to some degree from bidding the amounts that are more than what the creator needs.

Another limitation of the model is the binary-type-funder set-up. Relaxing this feature of the model and allowing for multiple types of funders would be a major extension of the model, which would also be a major extension for the Strauzs (2016) model. And if I allow the number of types to go to infinity, eventually I am dealing with an elastic demand. In that case, three other things will change in the model. First, the relationship between valuation and bidding choice will break down. In other words, having an elastic demand uncouples the relationship between being bidders and having high valuations, because facing an elastic demand, a threshold mechanism does not appear to be optimal among all possible mechanisms upon a first look. Second, the creators will no longer receive all social surplus ex-ante. The funders will always have some information rents left for themselves with an elastic demand curve. The real life observation that many creators often set up a price menu for the funders to choose from indicates the creators, recognizing an elastic demand, are trying to extract as much information rent from the funders as possible. Lastly, the distribution I used for modeling the valuation system will not be suitable anymore under an elastic demand framework. This extension will be a major improvement and is reserved for future research.

In the original model, when updating the crowdfunding participants' beliefs, I only perform one step Bayesian update. This implicitly implies that all funders cannot see how many bidders are already there when they determine whether to bid or not. The platform essentially applies a blind bidding scheme, where no participant is able to observe the progress of the capital raising activity for this project unless the project gets initialized. If I relax this feature and allow for multiple updates for the funders' beliefs regarding others preferences, I will be able to study the potential herding behaviors and bystander effects based on the observation made by Agrawal, Catalini, and Goldfarb (2014). They concluded in their paper that "funding propensity increases with accumulated capital and may lead to herding", and there is also a possibility one observes "a reduction in the propensity to fund by new individuals because of the perception that the target will be reached regardless."

One more extension I can make is to consider a nonlinear relationship between α and x. This implies the platform is able to let the creator set multiple bid levels x and allow for different α for each individual bid level x. This is more suitable in a case where there exist multiple types of funders, and essentially this extension is like offering a price menu in a reward crowdfunding case. For a study like this, one can turn to the paper written by Hu, Li, and Shi (2015).

5 Conclusion

In this thesis, I set up a model examining the possible implications of the recent trend that reward crowdfunding platforms start to partner with equity crowdfunding platforms. Based on the Strauzs (2016) model, the model studied the case where the creator faces a credit constraint and is unable to reach the entire market in the first place. The model constructs a platform which combines both reward-based crowdfunding and equity-based crowdfunding, and assumes the creator is able to set up an initialization rule which includes a threshold number of bidders, T, a bid x, and an equity share α. Using β distribution to model the funders valuations, I found several interesting results from the model. First of all, the credit constraint will always be satisfied, and when the investment cost is relatively small compared to the entire market size, the creator can reap all the expected social surplus ex-ante, and the result is socially optimal. Secondly, the platform is able to offer lower cost of capital which helps the creator overcome her initial credit constraint, and a demand signal which will be more accurate with a larger size of crowdfunding population. Thirdly, facing a higher investment cost which makes the project not always profitable ex-ante, the creator conditions her investment choice on successful observation of her expected demand signal ex-ante, provided that the creator is not allowed to adjust her investment decision ex-post. Additionally, the equity stake by which the creator induces the high type funders to bid plays an important role when the creator decides what the optimal threshold is. The creator weights the value from an extra bid against the equity cost of acquiring it when she sets up the threshold. Moreover, a project being objectively promising is very different from being subjectively promising, in the sense that the creator is likely to set herself up for failure in the latter case even in the case where the project is always profitable ex-ante. Lastly, the model predicts that how the creator gives back the equity does not affect the creator's ex-ante optimal choice or her ex-ante expected utility.

Appendix A

Major Crowdfunding Platforms in North America and Europe

Name	Funding Strategy	Initialization Rule	Other Features
Indiegogo	Reward	Both	Partnered with MircroVentures
Kickstarter	Reward	Fixed	N/A
Patreon	Reward	Flexible	Aiming at artists and innovators
RocketHub	Reward	Flexible	Partnered with Bankroll Ventures
PledgeMusic	Reward	Both	N/A
Crowd Supply	Reward	Fixed	Aiming at Tech-related Projects
Experiment	Reward	Fixed	Aiming at Scientific Research
EquityEats	Reward	Flexible	Gift Cards as Reward for Restaurant
Fundable	Reward & Equity	Fixed	N/A
MicroVentures	Equity	N/A	Partnership with Indiegogo
CircleUp	Equity	N/A	N/A
Crowdfunder	Equity	N/A	N/A
Grow VC	Equity	N/A	N/A
Angel List	Equity	N/A	N/A
SeedInvest	Equity	N/A	N/A
EquityNet	Equity	N/A	N/A
RealtyMogul	Equity	N/A	Real Estates Related
Generosity by Indiegogo	Donations	Flexible	0 Platform Fee
GoFundMe	Donations	Flexible	N/A
Crowdrise	Donations	Flexible	No Deadlines
YouCaring	Donations	Flexible	N/A
FundRazr	Donations	Flexible	N/A
DonorsChoose	Donations	Flexible	Build Classrooms, Schools, Buses for Children
YouCaring	Donations	Flexible	N/A
Plumfund	Donations	Flexible	N/A
GiveForward	Donations	Flexible	N/A
Kiva	Debt	Flexible	N/A
Funding Circle	Debt	Flexible	Aiming at Small Business
KickFurther	Debt	Flexible	Aiming at Small Business
Bolstr	Debt	Flexible	N/A
Lending Clubs	Debt	Flexible	N/A
Prosper	Debt	Flexible	N/A
RealtyShares	Debt & Equity	Flexible	Resturauants-Specific
Patch of Land	Debt	Flexible	Resturauants-Specific
SellABand*	Reward	Fixed	Bankrupted

* Used to be popular

Table 1: Results using Original Model Parameterization

With $n = 200, m = 16, I = 20$			
Ex-ante Expected Creator Payoff	T	x	α (%)
88.5229*	1*	20*	14.25*
88.3333	2	10	6.7086
87.4314	3	6.6667	4.1767
85.8170	4	5	2.9032
83.4902	5	4	2.1369
80.4510	6	3.3333	1.6268
76.6993	7	2.8571	1.2646
72.2353	8	2.5	0.9959
67.0588	9	2.2222	0.7902
61.1699	10	2	0.6290
54.5686	11	1.8182	0.5004
47.2549	12	1.6667	0.3962
39.2288	13	1.5385	0.3109
30.4902	14	1.4286	0.2404
21.0392	15	1.3333	0.1816
10.8758	16	1.25	0.1324

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 2: Results using Modified Model Parameterization

With $n = \mathbf{400}, m = 16, I = 20$			
Ex-ante Expected Creator Payoff	T	x	α (%)
187.869*	1*	20*	7.125*
186.373	2	10	3.3543
183.510	3	6.6667	2.0884
179.281	4	5	1.4516
173.686	5	4	1.0685
166.725	6	3.3333	0.8134
158.399	7	2.8571	0.6323
148.706	8	2.5	0.4980
137.647	9	2.2222	0.3951
125.222	10	2	0.3145
111.431	11	1.8182	0.2502
96.2745	12	1.6667	0.1981
79.7516	13	1.5385	0.1555
61.8627	14	1.4286	0.1202
42.6078	15	1.3333	0.0908
21.9869	16	1.25	0.0662

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 3: Results using Modified Model Parameterization

With $n = 200, m = 16, I = \mathbf{80}$			
Ex-ante Expected Creator Payoff	T	x	α (%)
32.0523	1	80	59.25
35.3922	2	40	29.0706
38.0196	3	26.6667	18.9181
39.9346	4	20	13.7903
41.1373	5	16	10.6847
41.6275*	6*	13.3333*	8.5986*
41.4052	7	11.4286	7.1010
40.4706	8	10	5.9754
38.8235	9	8.8889	5.1006
36.4641	10	8	4.4032
33.3922	11	7.2727	3.8363
29.6078	12	6.6667	3.3679
25.1111	13	6.1538	2.9760
19.9020	14	5.7143	2.6444
13.9804	15	5.3333	2.3613
7.3464	16	5	2.1176

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 4: Results using Modified Model Parameterization

With $n = 200, m = 16, I = \mathbf{150}$			
Ex-ante Expected Creator Payoff	T	x	α (%)
-33.8301	1	150	111.75
-26.3725	2	75	55.1595
-19.6275	3	50	36.1164
-13.5948	4	37.5	26.4919
-8.2745	5	30	20.6570
-3.6667	6	25	16.7324
0.2288	7	21.4286	13.9102
3.4118	8	18.75	11.7848
5.8824	9	16.6667	10.1293
7.6405	10	15	8.8065
8.6863	11	13.6364	7.7281
9.0196*	12*	12.5*	6.8349*
8.6405	13	11.5385	6.0853
7.5490	14	10.7143	5.4491
5.7451	15	10	4.9043
3.2288	16	9.375	4.4338

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 5: Results using Modified Model Parameterization

With $n = 200, m = \mathbf{25}, I = 20$			
Ex-ante Expected Creator Payoff	T	x	α (%)
92.9843	1	20	14.25
93.1453*	2*	10*	6.7315*
92.9829	3	6.6667	4.2165
92.4972	4	5	2.9547
91.688	5	4	2.1958
90.5556	6	3.3333	1.6895
89.0997	7	2.8571	1.3283
87.3205	8	2.5	1.0585
85.2179	9	2.2222	0.85
82.792	10	2	0.6848
80.0427	11	1.8182	0.5513
76.9701	12	1.6667	0.4416
73.5741	13	1.5385	0.3505
69.8547	14	1.4286	0.2741
65.812	15	1.3333	0.2093
61.4459	16	1.25	0.1541
56.7564	17	1.1765	0.1067
51.7436	18	1.1111	0.0660
46.4074	19	1.0526	0.0307
40.7479	20	1	0
34.5543	21	0.9524	0
28.13	22	0.9091	0
21.4679	23	0.8697	0
14.562	24	0.8333	0
7.40741	25	0.8	0

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 6: Results using Modified Model Parameterization

With $n = 200, m = 16, I = 20, F = \mathbf{10}$			
Ex-ante Expected Creator Payoff	T	x	α (%)
87.3464*	1*	20*	14.25*
85.9804	2	10	6.7086
83.9020	3	6.6667	4.1767
81.1111	4	5	2.9032
77.6078	5	4	2.1369
73.3922	6	3.3333	1.6268
68.4641	7	2.8571	1.2646
62.8235	8	2.5	0.9959
56.4706	9	2.2222	0.7902
49.4052	10	2	0.6290
41.6275	11	1.8182	0.5004
33.1373	12	1.6667	0.3962
23.9346	13	1.5385	0.3109
14.0196	14	1.4286	0.2404
3.3922	15	1.3333	0.1816
-7.9477	16	1.25	0.1324

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 7: Results using Modified Model Parameterization

With $n = 200, m = 16, I = 20$ and Modified α			
Ex-ante Expected Creator Payoff	T	x	α (%)
88.5229*	1*	20*	153*
88.3333	2	10	72.9
87.4314	3	6.6667	46.1429
85.8170	4	5	32.7273
83.4902	5	4	24.6522
80.4510	6	3.3333	19.25
76.6993	7	2.8571	15.3771
72.2353	8	2.5	12.4651
67.0588	9	2.2222	10.1852
61.1699	10	2	8.3571
54.5686	11	1.8182	6.8558
47.2549	12	1.6667	5.6
39.2288	13	1.5385	4.5335
30.4902	14	1.4286	3.6161
21.0392	15	1.3333	2.8182
10.8758	16	1.25	2.1177

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 8: Results using Modified Model Parameterization

With $n = 200, m = 16, I = 20, a = \mathbf{10}, b = \mathbf{10}$			
Ex-ante Expected Creator Payoff	T	x	α (%)
87.9383*	1*	20*	18.1224*
87.89	2	10	8.5843
87.8739	3	6.6667	5.4049
87.8658	4	5	3.8152
87.861	5	4	2.8614
87.8578	6	3.3333	2.2256
87.8555	7	2.8571	1.7713
87.8537	8	2.5	1.4307
87.8524	9	2.2222	1.1658
87.8513	10	2	0.9538
87.8504	11	1.8182	0.7804
87.8497	12	1.6667	0.6359
87.8491	13	1.5385	0.5136
87.8486	14	1.4286	0.4088
87.8481	15	1.3333	0.3179
87.8477	16	1.25	0.2385

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

Table 9: Results using Modified Model Parameterization

With $n = 200, m = 16, I = 20$, with Creator Prior $\beta(5,1)$			
Ex-ante Expected Creator Payoff	T	x	α (%)
87.6178	1	20	14.25
126.65	2	10	6.7086
140.039	3	6.6667	4.1767
146.821	4	5	2.9032
150.762	5	4	2.1369
153.044	6	3.3333	1.6268
154.057*	7*	2.8571*	1.2646*
153.843	8	2.5	0.9959
152.217	9	2.2222	0.7902
148.81	10	2	0.6290
143.067	11	1.8182	0.5004
134.234	12	1.6667	0.3962
121.335	13	1.5385	0.3109
103.142	14	1.4286	0.2404
78.1394	15	1.3333	0.1816
44.492	16	1.25	0.1324

* Maximum Ex-ante Creator Expected Utility and Set of Maximizers

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