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The inverted U-shaped relationship between crowdfunding success and reward options and the moderating effect of price differentiation

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Abstract
Purpose – The paper is to explore crowdfunding success determinants from the reward menu design aspect, distinguishing from extant studies focusing on characteristics of project creators or crowdfunding projects and funding dynamics. Both the number of reward options and price differentiation of rewards are considered.
Design/methodology/approach – The authors use the quadratic model to identify a curvilinear relationship between the number of reward options and crowdfunding success, by running regressions on data collected from one of the most influential reward-based crowdfunding platforms in China. In addition, they explore the moderating effect of price differentiation on the curvilinear relationship.
Findings – The authors find an inverted U-shape relationship between the number of reward options and the optimal number of options is around 10. In addition, they find that the curvilinear relationship is moderated by reward price differentiation.
Practical implications – This paper has managerial implications for crowdfunding project creators and platform managers. To achieve better crowdfunding outcomes, a proper number of reward options with diversified reward prices should be provided.
Originality/value – The paper contributes to the literatures in antecedents of crowdfunding success from reward menu design aspect based on theories in investment and purchasing decision making. It is different from existing studies focusing on the characteristics of project creators and crowdfunding projects or funding dynamics. It also parallels retirement contribution plan design studies by exploring the reward menu design in the crowdfunding context.

Keywords Crowdfunding, Reward menu design, Inverted U-Shape, Reward options, Price differentiation
Paper type Research paper

1. Introduction
Crowdfunding has become an important alternative financial approach for small entrepreneurs and medium-sized firms. It allows entrepreneurs to raise a small amount of funds from a large number of individuals, through a crowdfunding platform and avoids high interest rates and barriers associated with conventional forms of funding. There are mainly

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four types of crowdfunding platforms – reward-based, debt-based, equity-based and donation-based platforms – differing from each other by different returns provided to backers. In this paper, we explore reward-based crowdfunding projects, which provide rewards as returns to backers. The rewards in one crowdfunding project are usually products or services related to the project and are provided in different quality and prices. A detailed case of reward-based crowdfunding project is provided in Appendix. With the convenience for small startups to raise money, crowdfunding has opened up a brand new market with high value. Since its infancy, the crowdfunding volume has increased to US$5319.2 million in 2018 (Statista, 2019). Despite the increasing volume of crowdfunding, the success rate has remained modest, e.g. the average success rate of world's largest crowdfunding platform, Kickstarter, was only 36.96% in 2018.

Therefore, researchers have focused on the antecedents of crowdfunding success, mostly from project creators' characteristics crowdfunding projects' characteristics and investment dynamics. More specifically, representative studies of crowdfunding success factors include project creators' social capital (Bapna, 2019; Beier and Wagner, 2015), gender bias (Chen *et al.*, 2020; Gafni *et al.*, 2019b), culture and geography differences (Burtch *et al.*, 2013; Lin and Viswanathan, 2016), descriptions styles of projects' pitches (Dorfleitner *et al.*, 2016; Gafni *et al.*, 2019a; Zhou *et al.*, 2018), and information cascades among individual investors (Vismara, 2018) .

Although factors influencing crowdfunding success go beyond the attributes of projects, creators and investment dynamics, there is a marked paucity in studying characteristics of reward menu as an additional mechanism that influences crowdfunding success (Cai *et al.*, 2017; Hu *et al.*, 2015). One common interest in reward menu is the effect of the number of reward options on project success. However, extant studies in this area are not conclusive, and the results from different studies are contradictory. Some researchers find that the number of reward options has a positive effect on crowdfunding success (Kunz *et al.*, 2017; Zhou *et al.*, 2018) because a wider range of choices increases the likelihood that backers will find a preferred option (Baumol and Ide, 1956; Lancaster, 1990) and because of better price discrimination (Hardy, 2013). On the other hand, researchers also find a negative interaction between the number of reward options and crowdfunding success (Chen *et al.*, 2016; Leite and Moutinho, 2012) because of information overload from choice proliferation (Agnew and Szykman, 2005; Kida *et al.*, 2010). In addition, other studies find that the effect of the number of reward options on crowdfunding success remains implicit (Frydrych *et al.*, 2014).

These results posit a confusing phenomenon for academia and industry. Considering either the decision freedom effect or the information overloading effect may occur depending on the size of the reward menu, our study tries to answer whether there exists an inverted U-shaped relationship between the number of reward options and crowdfunding outcome and how this relationship is moderated by prices of the rewards.

To explore our research questions, we collect observational data from *Zhongchou.com*, one of China's most impactful reward-based crowdfunding platforms. Since its inception in 2013, *Zhongchou* had hosted more than 68,000 projects and solicited more than 250 million Renminbi (RMB for abbreviation) from approximately 1.6 million backers in 2017. *Zhongchou* host crowdfunding projects in different categories, including agriculture, publishing, entertainment, art, technique, charity and others. Our observational period is from January 2014 to December 2015. In our observation period, we collected data from approximately 9,314 projects, including the projects' attributes, project creators' information and the crowdfunding outcomes of these projects.

Our empirical analysis finds an inverted U-shaped relationship between the number of reward options and the success rate, with an optimal number of reward options around 10. When the number of reward options is low, an enlarged set of choices provides more freedom of choice for backers and enables them to find their optimal option. However, if the choice set is too large, information overload from choice proliferation occurs because backers must process a large cognitive load for decision making. In addition, we find that reward price differentiation moderates the curvilinear relationship between the number of reward options and crowdfunding success because differentiated prices can serve as diagnostic cues when comparing unfamiliar choices in the crowdfunding context.

This paper adds to the literature on crowdfunding success determinants from a new perspective, reward menu design, which is distinct from existing studies focusing on characteristics of creators and projects or investing dynamics. It also parallels studies in pension plan design by exploring the rewards menu design in the crowdfunding context. In addition to the theoretical contribution, this paper also has managerial implications for crowdfunding project creators and platform managers. To achieve better crowdfunding outcomes, a proper number of reward options with dispersed reward prices should be provided.

2. Literature review

2.1 Antecedents of crowdfunding success

Researchers have investigated crowdfunding success factors broadly since a low success rate remains an important issue for most crowdfunding platforms. Except few studies exploring this issue from platform level, including the effect from regulation policy uncertainty (Li *et al.*, 2017), the certification effect from venture capital (Li *et al.*, 2020) or the due diligence policy of the platform (Cumming *et al.*, 2019), most extant studies explore crowdfunding success determinants from project level and can be categorized into three aspects by the three relevant entities engaged in crowdfunding process: project creators, crowd backers, and crowdfunding projects.

Studies on project creators find that the creator's actions on the website, the signals about their human and social capitals and reputation formation have positive effects on crowdfunding success. More specifically, the project creators' actions, including interacting with backers and updating project progress, display their endeavors and establish credibility and legitimacy during the crowdfunding process (Block *et al.*, 2018; Wang *et al.*, 2018). Other studies find that the positive signals about the project creators' human and social capitals have a positive effect on crowdfunding success, which includes their educational information (Ahlers *et al.*, 2015; Piva and Rossi-Lamastra, 2018), external endorsement from third-party authorities (Bapna, 2019; Ralcheva and Roosenboom, 2016), and their social network information (Ge *et al.*, 2017; Vismara, 2016). In addition, entrepreneur reputation formation through past delivery performance and prior crowdfunding outcomes affects capital formation outcomes organically (Li and Martin, 2019).

A second stream of studies about backers investigates the dynamic influence between backers' contribution behaviors (Burtch *et al.*, 2013, 2014a) and the geography (Lin *et al.*, 2013) or cultural distances (Burtch *et al.*, 2014b) between the project creator and the backers. The effect of dynamic contribution behaviors among backers has been broadly investigated, including the findings of the rational herding (Zhang and Liu, 2012), the prism effect from friendship (Liu *et al.*, 2015) and observational learning from existing contributions (Burtch *et al.*, 2013). Especially, the actions of high-profile investors and large investment during the early stages of funding cycle lead to higher crowdfunding success (Vismara, 2018). In addition, studies on the distances between project creators and backers from both cultural and geographical aspects find that distance has a negative effect on crowdfunding outcome even though the Internet may free the creators and the backers from the restriction of distances (Burtch *et al.*, 2014b; Lin *et al.*, 2013).

A third stream of studies focuses on the aspect of crowdfunding project characteristics, which include project pitches, target amount, funding duration and project type. A relatively comprehensive study of the characteristics of crowdfunding projects from Chen *et al.* (2016) proposes a theoretical framework for crowdfunding appeals. Through a regression-based study of a stratified sample of 200 campaigns, they find guilt appeals, utilitarian product types, an emotional message frame and reward tiers are positively and significantly related to the ultimate funding level. In line with this study, Zhou *et al.*, (2018) use the text mining method to find the relationship between crowdfunding success and the project description (Zhou *et al.*, 2018). They find that antecedents from the content (length, readability and tone) and trustworthiness indicators (past experience and past expertise) of project descriptions are significantly related to crowdfunding success. Similar study explores description-text related soft information in debt-based crowdfunding and draws the conclusion that spelling errors, text length and mentioning of positive emotion evoking keywords predict the funding probability (Dorfleitner *et al.*, 2016). Besides, self-presentation in project pitches is associated with higher levels of trust and has a positive effect on crowdfunding success (Gafni *et al.*, 2019a). In addition to the text analysis in project description part, videos have been examined to increase success probability of loan because of increased creditworthiness and reduced transaction risk (Wang *et al.*, 2019).

Despite studies from the above three aspects, researchers also investigate the relationship between reward menu design and crowdfunding success. Related studies have investigated the number of reward options (Chen *et al.*, 2016; Zhou *et al.*, 2018), the limitedness of rewards (Weinmann *et al.*, 2017), middle option bias (Simons *et al.*, 2017), the decoy effect of similar rewards (Tietz *et al.*, 2016) and hybrid funding schemes (Cai *et al.*, 2017; Du *et al.*, 2019). However, among these studies, researchers find different results of the effect of the number of reward options. On the one hand, extant studies find a positive relationship between the number of reward options and crowdfunding success (Kunz *et al.*, 2017; Zhou *et al.*, 2018). On the other hand, studies from Chen *et al.* (2016) and Leite and Moutinho (2012) find an opposite effect, a significant negative relationship. However, other studies find that the relationship is implicit and not significant (Frydrych *et al.*, 2014). Based on the inconclusive findings about the relationship between crowdfunding success and the number of reward options, we try to determine the reasons for the contradictory findings and obtain a cohesive result anchored in the literature of assortment size and assortment pricing.

2.2 Assortment design

Economists, marketers and consumer behaviorists have broadly studied the effects of assortment size. Both positive and negative effects of enlarging assortment size are examined.

On the one hand, researchers study the positive effect of large assortment size from perspective including consumers' utility and decision efficiency as well as the performance of brands or stores. Utility studies have found that a larger assortment size increases the chance for an optimal choice (Wright and Barbour, 1975) or increases the probability of a perfect match (Baumol and Ide, 1956; Hotelling, 1929), offering consumers the psychological value of the freedom to choose (Reibstein *et al.*, 1975) or satisfying their innate desire to consume different alternatives (McAlister, 1982). Studies in decision efficiency have found that a large assortment size maintains the flexibility inherent in a varied assortment (Kahn and Lehmann, 1991), offers greater efficiency in identifying the available alternatives (Betancourt and Gautschi, 1990; Messinger and Narasimhan, 1997), and hence helps consumers make the final choice (Glazer *et al.*, 1991). In addition to the studies from the consumer perspective, other studies focus on the effect of assortment size on the performance of the brand or the store. They find that the reduction in assortment reduces overall store sales and decreases both sales frequency and quantity (Borle *et al.*, 2005; Sloot *et al.*, 2006). Researchers also find that the number of brands offered in a retail assortment has a positive effect on store choice (Briesch *et al.*, 2009) and brand choice (Berger *et al.*, 2007).

Despite the benefits from more options, researchers propose information overloading from choice proliferation by suggesting that the overabundance of options may lead to less motivation to make a final decision (Fasolo *et al.*, 2007; Mick *et al.*, 2004; Mogilner *et al.*, 2008). One stream of studies explores the negative consequences on consumers of choice proliferation, which induces failure to make a final choice (Sethi-Iyengar *et al.*, 2004), decreased satisfaction with the chosen option (Chernev, 2003a) or an increase in negative emotions, such as disappointment and regret (Schwartz, 2000). Another stream of studies tries to answer the mechanisms of choice proliferation's effects on consumers' final decisions. Shafir *et al.* (1993) find that the presence of too many options decreases differentiation between options and becomes barrier for consumers to make the best option. In line with Shafir *et al.*'s studies, Messner and Wänke (2011) also find that evaluating a larger assortment size requires more cognitive effort, which frustrates consumers who must compare options among a complex assortment with different attributes, and in turn induces the fear of not being able to choose the best option (Iyengar *et al.*, 2006).

2.3 Pension plan studies

In financial area, similar researches with the assortment design studies are the researches in studied pension design. Pension plans share similarities with crowdfunding rewards menus in providing several options for investors to choose. However, the options in pension plans are funds but the options in rewards menus are products and services related to the crowdfunding projects.

Related pension plan studies examine investors' investing strategies and investment behaviors. Especially, effects of the fraction of equity funds and the total number of funds in the plan are examined. Benartzi and Thaler (2001) find that the proportion invested in stocks depends on the proportion of stock funds in the plan because investors' diversification heuristic leads to the "1/n" strategy: "dividing contributions evenly across the funds offered". However, Huberman and Jiang (2006) find that the tendency of allocating contributions evenly across funds weakens with the number of funds used and that participants' propensity of contributing to equity funds is not very sensitive to the equity funds fraction when the number of funds in the pension plan is large. In line with this conclusion, studies also find that large choice sets lead to stronger preference for simple and easy-to-understand options and hence investors allocate large portion of assets into money markets and bond funds at the expense of equity funds (Iyengar and Kamenica, 2010). Others explore the conditions of large choice sets' negative effect on investment decision and find that the negative effect applies to less experienced investors and more experienced investors prefer a larger funds set (Kida *et al.*, 2010).

3. Hypotheses development

Researchers pay attention to the relationship between the number of reward options and crowdfunding success, since reward hunting is one of the main contribution motivations in reward-based crowdfunding platforms (Gerber and Hui, 2013). However, there are two competing findings about the effect of the reward options. One group of researchers believes in a positive effect of the number of reward options because of the wider range of choices to satisfy the diverse contribution motivations (Kunz *et al.*, 2017; Zhou *et al.*, 2018), since the backers have a variety of incentives to support (Gerber and Hui, 2013). The opposite side believes a negative relationship exists between crowdfunding success and the number of reward options because of information overloading (Chen *et al.*, 2016; Leite and Moutinho, 2012), which causes the backers' inability to locate what is relevant and their overlooking of what is most crucial among relevant data (Herbig and Kramer, 1994).

To summarize, the above analysis suggests that when the number of reward options is few, adding to the number of reward options enables backers to find their optimal option and provide them with the psychological benefits of having more choices. However, when the number of reward options is high, backers are faced with too many options, and in hence, information overloading discourages them from making a final decision. Hence, we hypothesize the following:

H1. There exists an inverted U-shaped relationship between the success rate and the number of reward options.

In consumer behavior studies, researchers have found that price is one of the most commonly used cues to infer products quality based on the rationale that higher price reflects finer design and better materials of the product. Empirical research also finds that prices are positively related with both the actual quality (Lichtenstein and Burton, 1989) and the perceived quality of the products (Teas and Agarwal, 2000). In addition, prices are used as criteria to judge products' quality and facilitate purchase decisions when consumers are unfamiliar with the products. Researchers have found differentially priced assortment leads to higher purchase probability and choice satisfaction when consumers are uncertain of their preferences on products' non-price attributes (Chernev, 2006; Choi *et al.*, 2018), because consumers are likely to use prices as diagnostic cues for making inferences under high preference uncertainty circumstance (de Langhe *et al.*, 2014). In this paper, we use Price Differentiation to indicate the extent of price dispersion of reward prices, which is calculated as the coefficient of variance of reward prices.

In Hypothesis 1, we argue that the inverted u-shaped relationship between crowdfunding success and the number of reward options is caused by the tradeoffs between the marginal benefits and costs of additional alternative.

In the benefits aspect, additional option increases the chance of finding the close matches to optimal choice (Baumol and Ide, 1956; Wright and Barbour, 1975) and provides the perception of choice freedom (Reibstein *et al.*, 1975). However, the marginal benefits from additional option tend to decrease with the increase in total number of options (Chernev and Hamilton, 2009). When taking price into consideration, more dispersed prices reflect more differentiated quality of products and lead to higher benefits at the same number of options. More intuitively, we provide Figure 1 to facilitate illustrations. On the left side of Figure 1, the Benefits-High PD and Benefits-Low PD lines are the benefits-options relationships under high/low price differentiation circumstances.

In the costs aspect, the cost of additional option is the increased cognitive load of evaluating the options (Messner and Wänke, 2011). And the marginal cost is increased with the number of options if evaluating options concerns comparisons between any two options. One source of the cognitive load is from the uncertainty of preferences on non-price attributes of products (Chernev, 2003b). Crowdfunding applies to the preferences uncertainty circumstance because the rewards are usually new to the market. However, cognitive load caused by preference uncertainty can be mitigated through using differentiated prices as diagnostic cues for inference making and simplifying decision making (Chernev, 2006; Choi *et al.*, 2018). Hence, more dispersed prices leads to lower evaluating cost at the same number of options. On the left side of Figure 1, the Costs-High PD and Costs-Low PD lines are the costs-options relationships under high/low price differentiation circumstances. Interactions A and B are the points when the net benefits comes to 0 under the high/low price differentiation circumstance. A simple description of the relationships between net benefits and the number of reward options under high/low price differentiation circumstances is provided on the right side of Figure 1. Therefore, we hypothesize the following:

H2. Price differentiation moderates the curvilinear relationship between the number of reward options and the crowdfunding success rate.

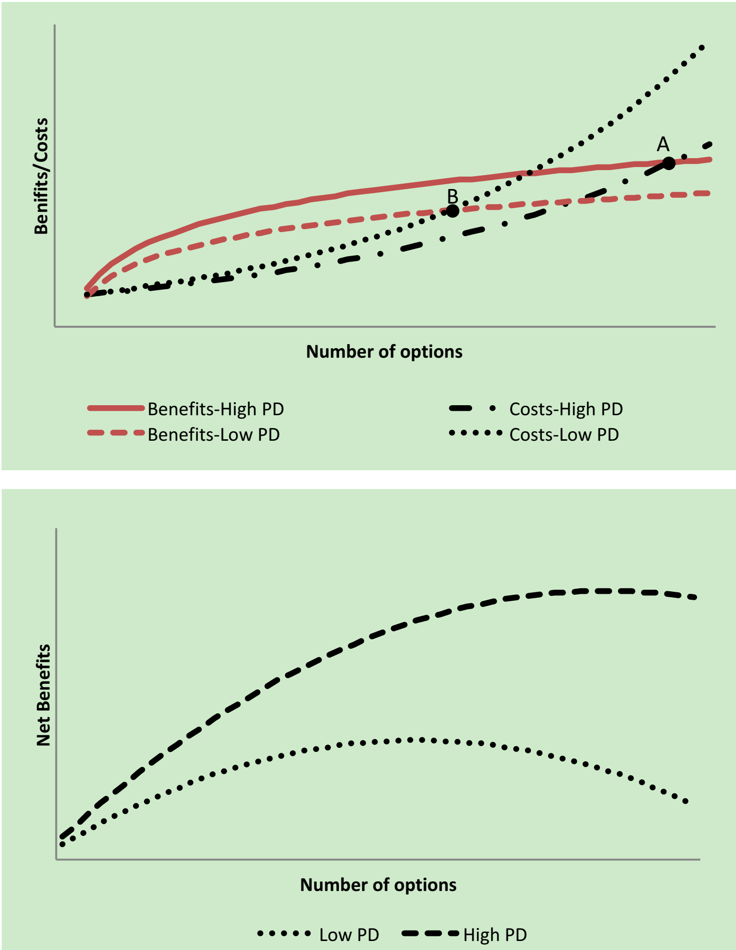

Figure 1.
Relationships between the number of options and the benefits/costs under the high/low price differentiation

4. Study context and data collection

4.1 Study context

We collect proprietary data from one of the largest crowdfunding platforms in China, *Zhongchou.com* [1]. The crowdfunding platform, "*zhongchou.com*" or "*zhongchou.cn*", established in February 2013, was a reward-based crowdfunding platform, belonging to the Fintech company NCF group (http://www.ncfgroup.com). It aimed at helping small entrepreneurs or individuals to fulfill their creative ideas by providing money solicited from the crowds. Since its inception in 2013, *Zhongchou* had hosted more than 68,000 projects and solicited more than 250 million RMB from about 1.6 million backers till 2017. As a reward-based crowdfunding platform, *Zhongchou* provided rewards as returns to backers and the rewards were usually products or services produced by the crowdfunding projects. This crowdfunding model is different from three other models, debt-based, equity-based, and donation-based platforms, which provide interest, equity and nothing as returns separately.

More specifically, on *Zhongchou*, project creators firstly launched their projects with detailed descriptions, funding goals and funding time. In the funding period, the potential backers browsed the projects and chose a project to support according to their own preferences. Only when the project raised enough money exceeding their funding goal before the funding deadline, the project creator could get the fund after deducting an administrative expense paid to the platform. Then the project creators would send the rewards to the backers after products preparation period.

4.2 Data collection

We collected our data through a web crawler, realized by PHP scripts in 2015. Our observational period was from January 2014 to December 2015. Data of 2013 was not included because the platform just started operation and went through a lot of changes and projects started in 2013 were also in a trial status and not representative enough. In our observation period, we collected data from 9,314 projects. The data we collected could be divided into three parts: the crowdfunding outcome, the attributes of the crowdfunding projects, and the information about the project creator.

In the crowdfunding outcome part, we collect the total amount of money pledged and the total number of backers of each project. In the project attributes part, we have data about the funding goal of each project, the start and end dates, the project category, the project content and the reward options. In the project creator characteristics part, we have information on date of joining the platform, geographical information, and whether they disclose their social media account (i.e. whether they are on Weibo, a blog, and WeChat), citizenship ID and business licenses.

5. Empirical methodology and variables

5.1 Curvilinear relationship between crowdfunding success and the number of reward options

We use a binary variable to depict whether a project is successful in raising money or not. When the total support amount is larger than the target amount, the project creator can obtain the entire support amount, and the binary variable is 1; otherwise, it is 0. We apply the linear probability model (LPM) for our main analysis. Although the LPM estimator has the drawbacks that the estimated probabilities are not bounded on the unit interval (Horrace and Oaxaca, 2006), the results for linear and logistic significance turn out to be nearly identical when the absolute percentage of the dependent variable is between 20% and 80% (in our case, the average success rate is 35%) (Angrist and Pischke, 2008; Hellevik, 2009; Long and Freese, 2014). The LPM model has the merits: the sum of components corresponds to the bivariate association and presents absolute differences in percentage points, facilitating the interpretation. We also apply logistic and probit estimations as alternative models for robustness checks.

The main model we use to detect the curvilinear relationship between crowdfunding success and the number of reward options is as follows:

$$\begin{aligned}\text{Success}_i = {} & \beta_0 + \beta_1 \cdot \text{Options}_i + \beta_2 \cdot \text{Options2}_i + \gamma \cdot \text{Project\_Attributes}_i \\ & + \delta \cdot \text{Initiator\_Atrributes}_i + \zeta \cdot \text{ProjectCategory}_i + \eta \cdot \text{StartMonth}_i \\ & + \theta \cdot \text{EndMonth}_i + \lambda \cdot \text{Locations}_i + \phi \cdot ID_i + \epsilon_i \qquad (1)\end{aligned}$$

Success_i represents whether the project raises enough money during the fund-raising period. Options_i is the *independent variable*, which denotes the number of reward options a crowdfunding project provides. Usually, a crowdfunding project creator defines different levels of reward options by different quantities or quality (Hu *et al.*, 2015). Each project has at least one reward option, and each reward option is given a predefined price and a specific configuration of tangible or intangible rewards. Options2_i is the square term of Options_i, by which we can examine the nonlinear relationship between crowdfunding success and the number of reward options. There are two sets of *covariates* in our model $\text{Project\_Atrributes}_i$ and $\text{Initiator\_Attributes}_i$, used to control for the attributes of project and the project creator characteristics. Besides, several categorical variables are included in our model to control potential unobserved within-group effects. These categorical variables include project type, the start and end months and project creators' locations as well as their ID types.

More specifically, regarding crowdfunding project attributes, we have the information about the monetary targets, the durations for fundraising, the project descriptions and the price ranges of the reward options. These variables are discussed broadly in the extant literature. In particular, funding goal is predefined by the project creator and is found to weaken the association between prior capital accumulation and visitor contribution (Burtch *et al.*, 2018). The duration of a project is the time length of funding period. A long duration can allow enough exposure to the backers, but a too long-duration can also serve as a signal that the creator lacks confidence (Mollick, 2014). In addition to the literature in the business venture area emphasizing the importance of business proposals (Carpentier and Suret, 2015; Macmillan *et al.*, 1985), studies in the crowdfunding area also point out the importance of the crowdfunding description by investigating the effect of different kinds of media (Koch and Siering, 2015; Wang *et al.*, 2019) and the sentiment expressed in the project description (Yuan *et al.*, 2016; Zhou *et al.*, 2018). We also include the price range variable in our model, which is defined as the range of lowest option price and highest option price of one project, Price range is broadly studied by researchers as a measure of price dispersion (Baye *et al.*, 2006).

In project creator attributes aspects, information of creators includes whether they disclose their social media information, citizenship ID or business license, and their geographical information as well as the day when they joined the platform. More specifically, we use a binary variable to describe whether project creator discloses their social media information for the following reasons. Project creators choosing to disclose their social media account may have unobserved homophily compared to those who do not. Besides, backers can be more informed of project creators by their social media account and infer the likelihood of crowdfunding success. In addition, inspired by literature in business venture which explores the relationship between the creators' pre-ownership and venture performance (Macmillan *et al.*, 1985; Stuart and Abetti, 1990), we construct the variable Experience as the time interval between project start day and the day when project creator joined the platform to represent creator's crowdfunding experience. ID information and geographical information are used as categorical variables in our model, which are discussed in the following separately.

We also include several vital categorical variables, including project start and end month, project type and creators' ID type as well as their locations. By including the start and end month, we control potential time effect. In addition, researchers have found that projects belonging to different categories may have different success rate (Belleflamme *et al.*, 2013; Cai *et al.*, 2017). Therefore, project type is included to control potential inter-category differences in success. In particular, on reward-based crowdfunding platforms, rewards are products or services related to the crowdfunding projects. Rewards of projects in the same project category may share similar patterns and be seen as in the same rewards type. Hence, project category variable also controls potential effect from different rewards types. For the ID type information, projects in *Zhongchou* can either be launched by an individual or an organization, which can be distinguished by the ID types (Individual Identification and/or Business License) disclosed to the platform. Lastly, we also control the effect of project creators' geographical information (Lin and Viswanathan, 2016) by classifying locations into east, middle, west and northeast of China.

5.2 The moderating effect of funding scheme price differentiation on the relationship between crowdfunding success and the number of reward options

We use the following model to detect the moderating effect of funding scheme price differentiation on the curvilinear relationship between crowdfunding success and the number of reward options:

$$\begin{aligned}\text{Success}_i = {} & \beta_0 + \beta_1 \cdot \text{Options}_i + \beta_2 \cdot \text{Options2}_i + \beta_3 \cdot \text{PriceDifferentiation}_i \\ & + \beta_4 \cdot \text{PriceDifferentiation}_i \cdot \text{Options}_i + \beta_5 \cdot \text{PriceDifferentiation}_i \cdot \text{Options2}_i \\ & + \gamma \cdot \text{Project\_Atrributes}_i + \delta \cdot \text{Initiator\_Attributes}_i + \zeta \cdot \text{ProjectCategory}_i \\ & + \eta \cdot \text{StartMonth}_i + \theta \cdot \text{EndMonth}_i + \lambda \cdot \text{Locations}_i + \phi \cdot ID_i + \epsilon_i \end{aligned} \tag{2}$$

$\text{PriceDifferentiation}_i$ denotes the extent of how the prices of reward options are differentiated from each other. We use the coefficient of variance to measure the differentiation of reward option prices, which is calculated as $\text{Price\_Std}_i/\text{Price\_Mean}_i$. Price_Std_i is the standard deviation of option prices in crowdfunding project i and Price_Mean_i is the mean of option prices in crowdfunding project i.

6. Empirical analysis and results

6.1 Summary statistics and correlation matrix

Table 1 provides the summary statistics of the variables used in this study. We have 9,314 observations of crowdfunding projects from several categories, including agriculture, entertainment, charity, technology, art, publishing, and others. The average success rate of our sample is 35%, which is considerably low and near the success rate disclosed by Kickstarter, the largest reward-based crowdfunding platform in the world. The average support amount per project is 14,813.60 RMB, with the average funding goal near 43,341.92 RMB. The average fulfilment ratio of the project is near 73%. In addition, the average time for the project to raise money is nearly 6 weeks. Of these projects, 69.82% are located in the eastern part of China and most of the project creators reveal their IDs to the platform.

Table 2 shows the correlative matrix of the dependent variables and independent variables. The proxy variables for success are significantly correlated with most of the independent variables at the 0.05 level. In particular, the two vital variables, the number of reward options and price differentiation, are positively correlated with crowdfunding success. In addition, the VIFs of the independent variables are all less than 10, which passes the multicollinearity test.

6.2 Empirical results

Before running the main models, we draw the histogram of our focal independent variable, the number of reward options. As in Figure 2, the distribution of the number of reward options is right-skewed, and the projects with fewer than 17 reward options account for 99.8% of all the projects. The project with the number of reward options larger than 17 only accounts for 0.2% of all the projects, but the largest number of reward options in our sample is 36. Hence, we trim our sample by excluding samples outside the interval of 1%–99% (Dixon, 1960) to exclude the effects from outliers. We also use the log transformation of other control variables to avoid non-normality.

We test our hypothesis in four steps. First, we run regression of all the control variables as the base model, Model 0; second, we add the number of reward options into the base model to

Variables	Variables definitions	Mean	SD	Min	Max	*N*
Success	The project raises enough money to meet its funding goal (yes = 1; otherwise = 0)	0.35	0.48	0	1	9,314
TotalSupport	Total money supported (in RMB)	14,813.60	116,308.00	0	5,660,024	9,314
FulfilmentRatio	Ratio of money supported to funding goal	0.73	2.45	0	99	9,314
Backers	Total number of backers in one project	42.59	233.44	0	7,983	9,314
AverageSupport	Average support per backer in one project	290.64	2,384.14	0	100,000	9,314
Text length	Text length in project description	5,790.38	4,433.66	159	60,458	9314
Pictures	Number of pictures in project description	10.44	7.81	0	94	9314
Videos	Number of videos in project description	0.29	0.72	0	16	9314
Options	Number of reward options of one project	6.07	2.18	1	36	9,314
Options2	Squared term of *Options*	41.58	35.32	1	1,296	9,314
Price range	Highest price minus lowest price	16,770.99	186,464.32	0	10,000,000	9,314
Price differentiation	Coefficient of variance of prices	1.38	0.47	0	5	9,314
Tagert amount	minimum funding Goa (in RMB)	43,341.92	215,543.48	10	10,000,000	9,314
Duration	Time length of funding period (in day)	41.12	22.87	1	322	9,314
Experience	Days between project start day and the day when project initiator joined the platform	593.32	640.56	0	916	9,314
Social network	Whether project creator discloses social network information (yes = 1; otherwise = 0)	0.15	0.35	0	1	9,314
Log support	Log transform of *TotalSupport*	5.93	3.43	0	16	9,314
Log fulfilment	Log transform of *FulfilmentRatio*	−2.14	2.10	−5	5	9,314
Log backers	Log transform of *Backers*	2.22	1.63	0	9	9,314
Log average	Log transform of *AverageSupport*	3.70	2.15	0	12	9,314
Log textlen	Log transform of *TextLength*	8.44	0.68	5	11	9,314
Log videos	Log transform of *Videos*	0.18	0.34	0	3	9,314
Log target	Log transform of *ProvisionPoint*	9.20	1.59	2	16	9,314
Log pricerange	Log transform of *PriceRange*	7.22	2.06	0	16	9,314
Log duration	Log transform of *Duration*	3.59	0.59	1	6	9,314

Table 1.
Summary statistics of variables

detect the general relationship between the number of reward options and crowdfunding success, shown as Model 1; third, we add the squared term of the number of reward options into Model 1 to detect the curvilinear relationship, shown as Model 2; last, we add the price differentiation variable and its interactions with both the number of reward options and the squared term of the number of reward options into Model 2 to detect the moderating effect of price differentiation on the curvilinear relationship between the number of reward options and the crowdfunding success, as shown in Model 3. The empirical results are displayed in Table 3.

6.2.1 Curvilinear relationship between crowdfunding success and the number of reward options. As shown in Table 3, in Model 1, we can see that projects with one more option generally have a 1.8% higher success rate, considering that the average success rate of the platform is only 35%, which suggests that the crowdfunding projects in this platform benefit from more options in general. After adding the squared term of the number of reward options

Table 2. The correlative matrix of variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)Success	1.000															
(2)LogSupport	0.601*	1.000														
(3)LogFulfilment	0.787*	0.845*	1.000													
(4)LogBackers	0.582*	0.793*	0.731*	1.000												
(5)LogAverage	0.469*	0.893*	0.706*	0.482*	1.000											
(6)Options	0.083*	0.211*	0.107*	0.211*	0.151*	1.000										
(7)Options2	0.074*	0.186*	0.088*	0.196*	0.129*	0.978*	1.000									
(8)NoOfPictures	0.000	0.087*	0.045*	0.061*	0.068*	0.162*	0.155*	1.000								
(9)PriceDifferentiation	0.023*	0.129*	0.010	0.173*	0.068*	0.351*	0.347*	−0.011	1.000							
(10)LogTextlen	0.115*	0.129*	0.125*	0.142*	0.137*	0.170*	0.161*	0.461*	0.077*	1.000						
(11)LogVideos	0.106*	0.079*	0.096*	0.077*	0.083*	0.110*	0.107*	0.074*	0.076*	0.160*	1.000					
(12)LogTarget	−0.203*	0.097*	−0.290*	0.039*	0.088*	0.206*	0.205*	0.070*	0.255*	0.039*	−0.012	1.000				
(13)LogPricerange	−0.013	0.130*	−0.048*	0.074*	0.152*	0.491*	0.468*	0.096*	0.650*	0.135*	0.077*	0.541*	1.000			
(14)LogDuration	−0.137*	−0.072*	−0.166*	−0.099*	−0.056*	0.132*	0.120*	0.043*	0.105*	0.037*	0.028*	0.210*	0.136*	1.000		
(15)Experience	−0.030*	−0.009	−0.065*	−0.098*	−0.106*	0.041*	0.033*	0.125*	−0.029*	−0.187*	−0.142*	0.125*	−0.020	−0.002	1.000	
(16)SocialNetwork	0.106*	−0.012	0.072*	−0.044*	0.006	−0.019	−0.016	−0.077*	0.001	0.046*	0.119*	−0.169*	−0.053*	0.051*	−0.230*	1.000

Note(s): * shows significance at the 0.05 level

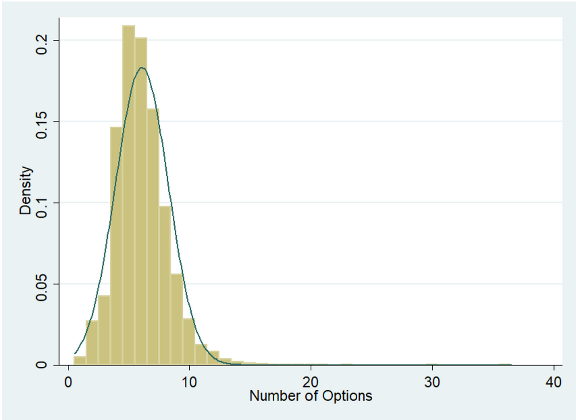

Figure 2.
The distribution of the number of reward options

in Model 2, the coefficient of the number of reward options is still positive and larger than that in Model 1. However the coefficient of the squared term is significantly negative, which means that after crowdfunding success arrives at a peak, adding one more option has a negative effect on crowdfunding success. In our case, the optimal number of reward options is around 10. More specifically, when the number of reward options is 2, adding one more option increases crowdfunding success by 5.2%, which accounts for 14.9% of the average success rate (35%). When the number of reward options is 10, adding one more option has almost no effect on crowdfunding success, increased by 0.4% in our case. When the number of reward options is 12, adding one more option decreases the crowdfunding success by 1.0%.

6.2.2 Moderating effect of funding scheme price differentiation on the curvilinear relationship between the number of reward options and crowdfunding success. Model 3 shows the moderating effect of price differentiation and the number of reward options. The coefficients of the two interaction terms are significant, which means that the price differentiation moderates the relationship between crowdfunding success and the number of reward options. To illustrate the moderating effect more intuitively, we develop graphs to exhibit the moderating effects in Figure 3. We divide the data set into high price differentiation campaigns and low price differentiation campaigns by 1 SD above and below the mean, which is a common practice in other studies (Faber and Walter, 2017; Richard *et al.*, 2004). Among the low price differentiation campaigns (−1 SD), the slope analysis yields an inverted U-shaped relationship between the number of reward options, which is in consistence with our assumption that the less differentiated prices cannot decrease the cognitive load for backers to make a final decision when there are too many unfamiliar choices. Among the high price differentiation campaigns (+1 SD), the slope analysis finds a positive relationship between the number of reward options and crowdfunding success. It could be explained that differentiated prices work as diagnostic cues to simplify the decision process and reduce the cognitive load for decision-making. Therefore, in this case, the optimal number of reward options is out of the actual range of the reward options in this sample and the relationship between crowdfunding success and the number of reward options are generally positive.

7. Robustness checks and endogeneity test

We use alternative models and alternative dependent variables to test the robustness of our results and perform a two-stage limited information maximum likelihood estimator to test any possible endogeneity problem.

Estimator: LPM Dv: Success	Model 0	Inverted U-shaped relationship Model 1	Model 2	Moderating effect Model 3
LogTextlen	0.058*** (0.007)	0.053*** (0.007)	0.052*** (0.007)	0.052*** (0.007)
LogVideos	0.099*** (0.015)	0.092*** (0.015)	0.092*** (0.015)	0.093*** (0.015)
LogPricerange	0.027*** (0.003)	0.016*** (0.003)	0.015*** (0.003)	0.018*** (0.004)
LogTarget	−0.072*** (0.004)	−0.069*** (0.004)	−0.068*** (0.004)	−0.069*** (0.004)
LogDuration	−0.098*** (0.009)	−0.104*** (0.009)	−0.106*** (0.009)	−0.106*** (0.009)
Experience	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
SocialNetwork	0.085*** (0.014)	0.086*** (0.014)	0.086*** (0.014)	0.086*** (0.014)
Locations	√	√	√	√
IDs	√	√	√	√
ProjectType	√	√	√	√
BeginMonth	√	√	√	√
EndMonth	√	√	√	√
Options	–	0.021***(0.003)	0.064***(0.012)	0.142***(0.039)
Options2	–	–	−0.003***(0.001)	−0.008**(0.003)
PriceDifferentiation	–	–	–	0.216*(0.092)
Options PriceDifferentiation*	–	–	–	−0.062*(0.027)
Options2 PriceDifferentiation*	–	–	–	0.004*(0.002)
Constant	0.767***(0.081)	0.761***(0.081)	0.670***(0.087)	0.400**(0.146)
R-squared	0.156	0.160	0.161	0.161
Observations	9,179	9,179	9,179	9,179

Note(s): + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 3.
Main analysis of the hypothesis

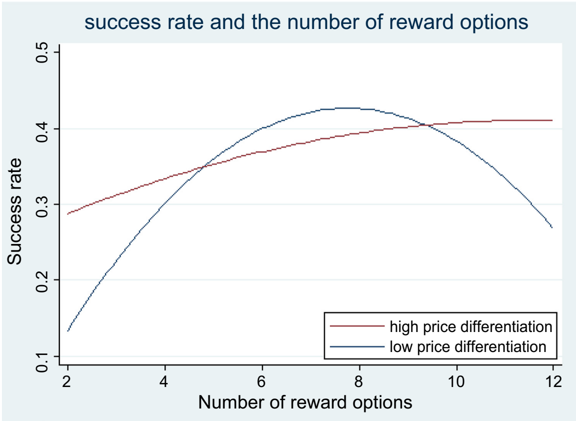

Figure 3.
Slop analysis of success rate and the number of reward options

7.1 Alternative estimators

We perform our main analysis using the LPM estimator for its merits in presenting absolute differences in percentage points and facilitating our interpretation. Here, we use the logistic model and probit model as alternative estimators to test the robustness of our results because the dependent variable is a binary variable. The results are shown in Table 4.

For the robustness checks of H1 (the first and the second columns), the coefficients of the squared term in both the logistic model (the coefficient is fitted for using the log of odds ratio as the dependent variable) and probit model are significantly negative, which are qualitatively the same as our main analysis using the linear probability model. In addition, the optimal number of reward options is around 9, which is quite close to the results in the main analysis. We also use logistic regression and logit regression to check the robustness of the results for the moderating effect (in the third and fourth columns): the interaction terms are also significant and in the same direction as the results in the main analysis. In conclusion, the results for the two hypotheses remain robust when we use the two alternative estimators.

7.2 Alternative dependent variables

Using the binary variable to identify the success of crowdfunding in the main model cannot capture the nuances of crowdfunding outcomes, so we use two alternative continuous variables to describe the success of crowdfunding projects: the total support amount and the fulfilment ratio. The fulfilment ratio is the ratio of the total support amount to the funding goal. When it is larger than 1, the crowdfunding project can obtain money; when it is less than 1, the project cannot obtain money. More specifically, Fulfilment_i or the completion ratio is defined as follows:

$$\text{Fulfillment}_i = \frac{\text{Total\_Support}_i}{\text{Funding\_Goal}_i}$$

which is broadly adopted in crowdfunding studies as the proxy for crowdfunding success (Carr, 2013; Chen *et al.*, 2016; Leite and Moutinho, 2012). The continuous variables capture more information than the yes-or-no binary variable and can compare the extent of how much the funding goal is fulfilled. Because the distribution of the total support amount and the fulfillment ratio are highly right-skewed, we use the log transformation of the two variables to obtain residuals that are approximately symmetrically distributed so that the patterns in the data are more interpretable (Tukey, 1977).

Table 4. Robustness checks by alternative estimators

Estimators: Logistic and probit	Inverted U-shaped relationship		Moderating effect	
Dv: Success	Logistic model	Probit model	Logistic model	Probit model
LogTextlen	0.284*** (0.039)	0.165*** (0.023)	0.281*** (0.040)	0.163*** (0.023)
LogVideos	0.428*** (0.073)	0.261*** (0.044)	0.432*** (0.073)	0.263*** (0.044)
LogPricerange	0.077*** (0.017)	0.048*** (0.010)	0.091*** (0.021)	0.056*** (0.013)
LogTarget	−0.362*** (0.020)	−0.214*** (0.012)	−0.365*** (0.021)	−0.216*** (0.012)
LogDuration	−0.528*** (0.045)	−0.317*** (0.026)	−0.527*** (0.045)	−0.316*** (0.026)
Experience	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
SocialNetwork	0.396*** (0.071)	0.240*** (0.043)	0.401*** (0.071)	0.242*** (0.043)
Locations	√	√	√	√
IDs	√	√	√	√
ProjectType	√	√	√	√
BeginMonth	√	√	√	√
EndMonth	√	√	√	√
Options	*0.339*** (0.063)*	*0.194*** (0.037)*	*0.775*** (0.209)*	*0.432*** (0.121)*
Options2	*−0.018*** (0.005)*	*−0.010*** (0.003)*	*−0.044** (0.015)*	*−0.024** (0.009)*
PriceDifferentiation	–	–	*1.194* (0.496)*	*0.662* (0.286)*
Options PriceDifferentiation*	–	–	*−0.341* (0.144)*	*−0.188* (0.084)*
Options2 PriceDifferentiation*	–	–	*0.021* (0.010)*	*0.011^{+} (0.006)*
Constant	−0.410 (0.455)	−0.206 (0.271)	−1.965* (0.797)	−1.065* (0.464)
R-squared	0.1137	0.1127	0.1144	0.1133
Observations	9,179	9,179	9,179	9,179

Note(s): + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

In addition, the total support amount is the product of the number of backers and the average support amount per backer. We also examine whether curvilinear relationships and the moderating effect exist between the number of reward options and the two intermediate variables for robustness checks.

As shown in Table 5, when we use the log of fulfillment ratio, total support amount, the log of the number of backers and the log of average support per backer as dependent variables separately, the coefficients in column (1) to (4) are qualitatively the same as the results in the main analysis, indicating that the inverted U-shaped pattern also occurs in the relationships of the number of reward options with the four alternative variables. In addition, the coefficients of the interaction terms in column (5) to (8) are also significant using the alternative variables as dependent variables separately, which are in the same direction as the results in the main analysis.

7.3 Endogeneity test

We employ the two-stage limited information maximum likelihood (LIML) estimator to test the potential endogeneity problem. The instrumental variables we use are the number of pictures in the project description part and its square term (Kelejian, 1971). When there are more reward options, the project creators tend to use more pictures to describe the rewards. Therefore the number of pictures is associated with the number of reward options. However, in *zhongchou.com*, the project description part also contains videos. Videos have been proved to play an important role on loan success in P2P platforms (Wang *et al.*, 2019). When videos and pictures coexist, the backers tend to refer to videos to make decisions rather than pictures. The literature in the educational and psychological areas finds the superiority of studying videos over static pictures (Arguel and Jamet, 2009; Höffler and Leutner, 2007). In addition, researches in the crowdfunding area also do not find any significant influence of the number of photos on crowdfunding success (Beier and Wagner, 2015; Chen *et al.*, 2016), which is consistent with our simple correlation analysis in Table 2. We also use more solid statistical tests to check the under-identification and weak instrument problems of the instrumental variable. The histogram of the number of pictures is quite right-skewed. Hence, we trim our data by excluding outliers of the number of pictures outside the interval of 2.5–97.5%.

First, we test whether the focal variables (the number of reward options and its square term) are exogenous with the Hausman test. The Hausman test statistic is 7.25 ($p < 0.05$), rejecting the null hypothesis that the focal variables are exogenous. Second, we use the number of pictures and its square term as the instrumental variables for the number of reward options and its square term, so the equation is exactly identified. Furthermore, for the under-identification test, the Kleibergen-Paap rk LM statistic is 15.72 ($p < 0.001$), rejecting the null hypothesis that the equation is under-identified. For the weak instruments test, the Cragg-Donald Wald F statistic is 11.38, exceeding its Stock-Yogo critical value of 7.03 (we can reject the null hypothesis under the i.i.d assumption by supposing we are willing to accept at most a rejection rate of 10% of a nominal 5% Wald test). The Kleibergen-Paap rk Wald F statistic is 8.02, exceeding the Stock-Yogo critical value of 7.03 again (we can also reject the weak instruments hypothesis when we drop the i.i.d assumption by supposing we are willing to accept at most a rejection rate of 10% of a nominal 5% Wald test). However, the Kleibergen-Paap rk Wald F statistic is still relatively small. Hence, we choose the LIML estimator to test the endogeneity problem because the LIML estimator is less biased, more efficient and performs better in weaker instruments (Angrist and Pischke, 2008).

We synthesize the first stage and second stage results of the LIML estimator and the results from LPM in Table 6. As we can see, the coefficients of the instrumental variables in the 1st stage are significant, suggesting the relevant relationships between the instrumental variables and the endogenous variables. Because we use the number of pictures and its

Table 5. Robustness checks by alternative dependent variables

Estimators: OLS	Inverted U-shaped relationship				Moderating effect			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DVs	LogFulfillment	LogSupport	LogBackers	LogAverage	LogFulfillment	LogSupport	LogBackers	LogAverage
LogText	0.265*** (0.031)	0.394*** (0.053)	0.139*** (0.024)	0.249*** (0.038)	0.264*** (0.032)	0.416*** (0.053)	0.164*** (0.024)	0.246*** (0.038)
LogVideos	0.372*** (0.062)	0.586*** (0.105)	0.235*** (0.048)	0.369*** (0.076)	0.371*** (0.062)	0.578*** (0.105)	0.230*** (0.047)	0.367*** (0.076)
LogPricerange	0.049*** (0.014)	−0.028 (0.023)	−0.078*** (0.011)	0.047** (0.017)	0.048** (0.017)	−0.136*** (0.029)	−0.197*** (0.013)	0.056** (0.021)
LogTarget	−0.421*** (0.016)	0.189*** (0.027)	0.061*** (0.012)	0.109*** (0.019)	−0.421*** (0.016)	0.220*** (0.027)	0.096*** (0.012)	0.106*** (0.020)
LogDuration	−0.504*** (0.037)	−0.779*** (0.062)	−0.357*** (0.028)	−0.350*** (0.045)	−0.506*** (0.037)	−0.804*** (0.062)	−0.383*** (0.028)	−0.350*** (0.045)
Experience	0.000*** (0.000)	0.000 (0.000)	0.001*** (0.000)	−0.001*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.001*** (0.000)	−0.000*** (0.000)
SocialNetwork	0.179** (0.061)	0.231* (0.102)	0.035 (0.046)	0.138 (0.074)	0.181** (0.061)	0.229* (0.102)	0.033 (0.046)	0.138 (0.074)
Locations	√	√	√	√	√	√	√	√
IDs	√	√	√	√	√	√	√	√
ProjectType	√	√	√	√	√	√	√	√
BeginMonth	√	√	√	√	√	√	√	√
EndMonth	√	√	√	√	√	√	√	√
Options	*0.520*** (0.051)*	*1.104*** (0.086)*	*0.447*** (0.039)*	*0.656*** (0.062)*	*0.922*** (0.165)*	*1.682*** (0.278)*	*0.776*** (0.125)*	*1.004*** (0.201)*
Options2	*−0.029*** (0.004)*	*−0.059*** (0.006)*	*−0.019*** (0.003)*	*−0.040*** (0.005)*	*−0.059*** (0.012)*	*−0.105*** (0.021)*	*−0.043*** (0.009)*	*−0.068*** (0.015)*
PriceDifferentiation	–	–	–	–	*0.908* (0.388)*	*1.691** (0.654)*	*1.367*** (0.293)*	*0.621 (0.472)*
Options PriceDifferentiation*	–	–	–	–	*−0.285* (0.114)*	*−0.364$^+$ (0.193)*	*−0.204* (0.087)*	*−0.238$^+$ (0.139)*
Options2 PriceDifferentiation*	–	–	–	–	*0.021** (0.008)*	*0.028* (0.014)*	*0.014* (0.006)*	*0.019$^+$ (0.010)*
Constant	−1.594*** (0.375)	−1.406* (0.633)	−0.083 (0.287)	−1.106* (0.456)	−2.822*** (0.631)	−3.510*** (1.065)	−1.661*** (0.478)	−2.008** (0.768)
R-squared	0.202	0.138	0.176	0.089	0.203	0.143	0.196	0.089
Observations	9,179	9,179	9,179	9,179	9,179	9,179	9,179	9,179

Notes(s): + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Estimator: LIML and LPM	Inverted U-shaped relationship LIML			LPM (Baseline regression)
	1st stage		2nd stage	
DVs	Options	Options2	Success	Success
LogTextlen	0.013 (0. 035)	0.042 (0.468)	0.049*** (0.020)	0.052*** (0.007)
LogVideos	0.238*** (0.055)	2.923*** (0.737)	0.085*** (0.019)	0.092*** (0.015)
LogPricerange	0.527*** (0.011)	6.492*** (0.143)	0.004 (0.016)	0.015*** (0.003)
LogTarget	−0.148*** (0.014)	−1.599*** (0.184)	−0.055*** (0.008)	−0.068*** (0.004)
LogDuration	0.271*** (0.032)	2.976*** (0.430)	−0.130*** (0.016)	−0.106*** (0.009)
Experience	0.001*** (0.000)	0.006*** (0.001)	0.000*** (0.000)	0.000*** (0.000)
SocialNetwork	−0.052 (0.053)	−0.868 (0.708)	0.073*** (0.017)	0.086*** (0.014)
Locations	√	√	√	√
IDs	√	√	√	√
ProjectType	√	√	√	√
BeginMonth	√	√	√	√
EndMonth	√	√	√	√
Options	*0.067*** (0.010)*	*0.709*** (0.138)*	*0.658** (0.254)*	*0.064*** (0.012)*
Options2	*−0.001** (0.000)*	*−0.009* (0.005)*	*−0.050** (0.020)*	*−0.003*** (0.001)*
Constant	1.497*** (0.347)	−13.940 (4.665)	-1.141^{+} (0.673)	0.670*** (0.087)
Observations	8,930	8,930	8,930	9,179

Summary of endogeneity test statistics	
Under identification test	
Kleibergen-Paap rk LM statistic	15.72
p-Value	0.000
Weak identification test	
Cragg-Donald Wald F statistic	11.38
Kleibergen-Paap rk Wald F statistic	8.02
Stock-Yogo weak ID test critical values: 10% maximal IV size	7.03

Note(s): (1) $+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$; (2) Observations Difference is caused by trimming the outliers of NoOfPicutres

Table 6.
The endogeneity test by LIML estimator

squared term as instrumental variables, it is not intuitive to check the relationships between endogenous variables and instrumental variables through the direction of the coefficients. When we consider the relationship between the number of reward options and the number of pictures, the result is shown in the first column of Table 6, which is an inverted U-shaped relationship. The maximal number of reward options occurs when the number of pictures equals 34. However, the largest number of pictures in the data after trimming the outliers is 31. Hence the relationship between the number of reward options and the number of pictures remains positive in the feasible region of the number of pictures. Meanwhile, when we consider the relationship between the square of the number of reward options and the square of the number of pictures, the relationship between them can be simplified as $y = \alpha \cdot \sqrt{x} + \beta \cdot x + \varepsilon$, where y is the square of the number of reward options and x is the square of the number of pictures. By the result shown in the second column of Table 6, the relationship between the square of the number of options and the square of the number of pictures is also inverted U-shaped and the maximal value of the square of the number of reward options occurs when $x = \alpha^2/4\beta^2$. In our case, it is when the number of pictures is 39, which is larger than the maximal number of pictures. Hence, the relationship between the square of the number of reward options and the square of the number of pictures is also positive in the feasible region of the number of pictures in our dataset.

In the 2nd stage, coefficients of the endogenous variables in the LIML are significant and of the same direction as the coefficients in the LPM estimator, which suggests that after resolving the endogeneity problem of our focal variables, the curvilinear relationship still exists between the number of reward options and crowdfunding success.

For the potential endogeneity problem of H2, as discussed in Bun and Harrison's theoretical paper in *Econometric Reviews*, the endogeneity bias can be reduced to 0 for the OLS estimator when the interaction term is considered and the coefficients of the interaction term are consistent (Bun and Harrison, 2019). Therefore, we only practice the LIML estimator to test the endogeneity problem for H1 as above.

8. Discussion and conclusion

This paper has several novel empirical findings for the reward menu design of crowdfunding projects. *First*, we examine the inverted U-shaped relationship between crowdfunding success and the number of reward options. When the number of reward options is relatively low, adding one more option has a marginally positive effect on crowdfunding performance because of the benefits of option value and optimal match. However, when the number of reward options is relatively high, adding one more reward option has a marginally negative effect on crowdfunding success because the imposed cognitive load on the backers discourages final decisions. *Second*, we find that the curvilinear relationship between crowdfunding success and the number of reward options is moderated by the price differentiation of the reward options. When the price differentiation is high, the differentiated prices of reward options increase the diversity perception of the rewards and serve as the diagnostic cue to reduce the cognitive load, which facilitate decision making even when the size of reward menu is large. However, when price differentiation is low, the diversity perception of the rewards is low and the cognitive load cannot be mitigated, which discourages decision making for comparing between similar options.

This paper adds to the literature in crowdfunding success determinants from the reward menu design aspects, based on theories in decision making for investment and purchasing. It is distinct from existing studies from perspectives of characteristics of creators and projects or investing dynamics, which are usually based on signal theory or herding behavior (Cai, 2018). This paper also parallels pension design studies by exploring reward menu design in the crowdfunding context. However, the reward menu design's effect on investing dynamics remains open for further researches. This study also has implications for crowdfunding creators and platform managers to take consideration of the proper number of reward options and a differentiated price menu.

Note

1. Zhongchou.com was shut down in 2019 because of market competition from big Internet companies in China, such as crowdfunding platforms of Taobao and JD, but it was a pioneer of Chinese crowdfunding platforms, among one of the earliest crowdfunding platforms. Some history pages could be obtained through searching "www.zhongchou.com" or "www.zhongchou.cn" on "wayback.archive.org", which is a nonprofit initiative of Internet Archive.

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Appendix

A case of crowdfunding project in Zhongchou.com

We provide a case of art crowdfunding project of Zhongchou.com. This project was launched by a Chinese zither amateur, started on October 31, 2014 and ended on December 30. It aimed at popularizing Chinese zither culture by renting or selling Chinese zithers to backers. The money raised was used to fulfill three goals: establishing a Chinese zither pavilion in Shanghai for Chinese zither teaching and playing skills communication; providing charitable shows of Chinese zither to popularize Chinese zither culture; a long term goal to establish a Chinese zither manufacturing society.

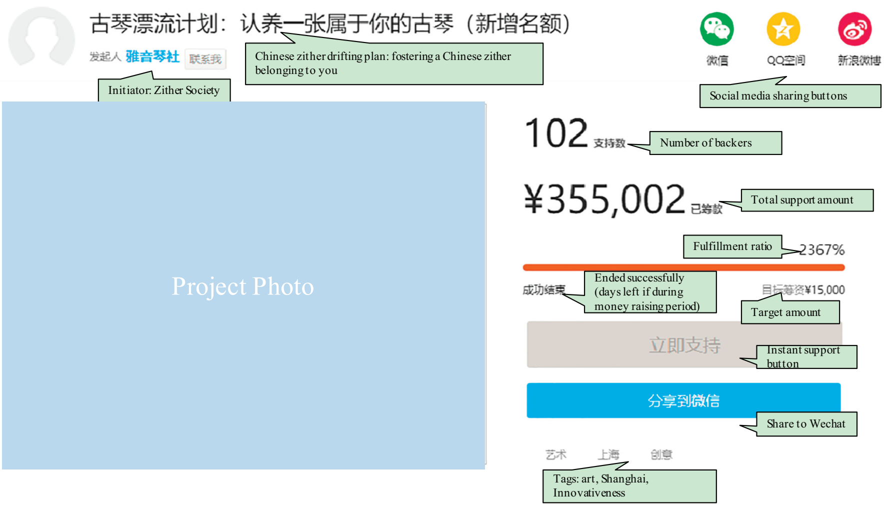
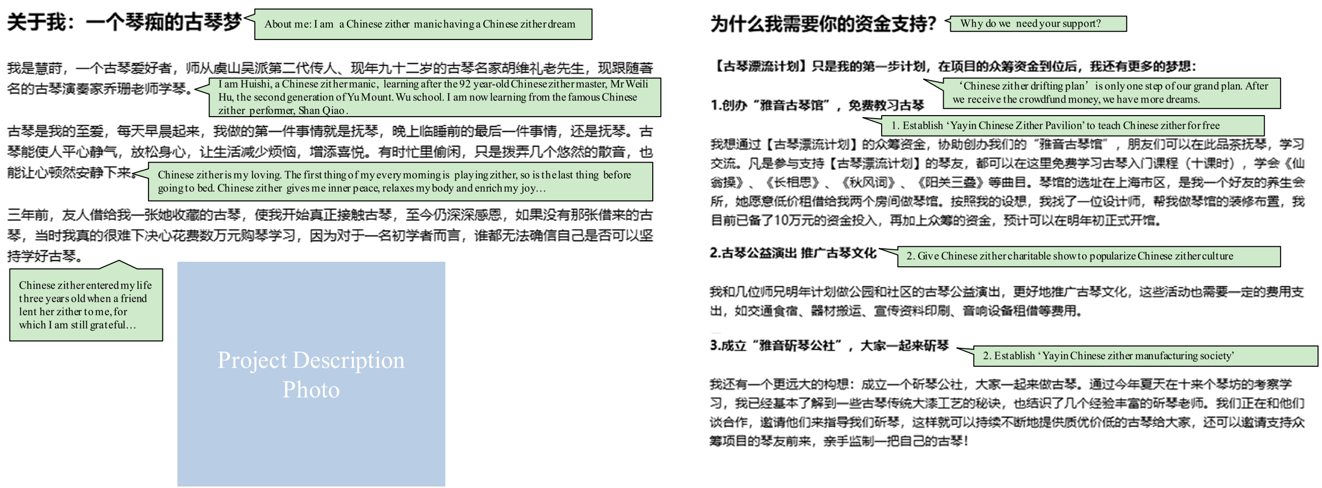


Figure A1.
Project overview



关于我：一个琴痴的古琴梦

About me: I am a Chinese zither manic having a Chinese zither dream

我是慧莳，一个古琴爱好者，师从虞山吴派第二代传人、现年九十二岁的古琴名家胡维礼老先生，现跟随著名的古琴演奏家乔珊老师学琴。

I am Huishi, a Chinese zither manic, learning after the 92 year-old Chinese zither master, Mr Weili Hu, the second generation of Yu Mount. Wu school. I am now learning from the famous Chinese zither performer, Shan Qiao.

古琴是我的至爱，每天早晨起来，我做的第一件事情就是抚琴，晚上临睡前的最后一件事情，还是抚琴。古琴能使人平心静气，放松身心，让生活减少烦恼，增添喜悦。有时忙里偷闲，只是拨弄几个悠然的散音，也能让心顿然安静下来。

Chinese zither is my loving. The first thing of my every morning is playing zither, so is the last thing before going to bed. Chinese zither gives me inner peace, relaxes my body and enrich my joy…

三年前，友人借给我一张她收藏的古琴，使我开始真正接触古琴，至今仍深深感恩，如果没有那张借来的古琴，当时我真的很难下决心花费数万元购琴学习，因为对于一名初学者而言，谁都无法确信自己是否可以坚持学好古琴。

Chinese zither entered my life three years old when a friend lent her zither to me, for which I am still grateful…

Project Description Photo

为什么我需要你的资金支持？

Why do we need your support?

【古琴漂流计划】只是我的第一步计划，在项目的众筹资金到位后，我还有更多的梦想：

‘Chinese zither drifting plan’ is only one step of our grand plan. After we receive the crowdfund money, we have more dreams.

1.创办“雅音古琴馆”，免费教习古琴

1. Establish ‘Yayin Chinese Zither Pavilion’ to teach Chinese zither for free

我想通过【古琴漂流计划】的众筹资金，协助创办我们的“雅音古琴馆”，朋友们可以在此品茶抚琴，学习交流。凡是参与支持【古琴漂流计划】的琴友，都可以在这里免费学习古琴入门课程（十课时），学会《仙翁操》、《长相思》、《秋风词》、《阳关三叠》等曲目。琴馆的选址在上海市区，是我一个好友的养生会所，她愿意低价租借给我两个房间做琴馆。按照我的设想，我找了一位设计师，帮我做琴馆的装修布置，我目前已备了10万元的资金投入，再加上众筹的资金，预计可以在明年初正式开馆。

2.古琴公益演出 推广古琴文化

2. Give Chinese zither charitable show to popularize Chinese zither culture

我和几位师兄明年计划做公园和社区的古琴公益演出，更好地推广古琴文化，这些活动也需要一定的费用支出，如交通食宿、器材搬运、宣传资料印刷、音响设备租借等费用。

3.成立“雅音斫琴公社”，大家一起来斫琴

2. Establish ‘Yayin Chinese zither manufacturing society’

我还有一个更远大的构想：成立一个斫琴公社，大家一起来做古琴。通过今年夏天在十来个琴坊的考察学习，我已经基本了解到一些古琴传统大漆工艺的秘诀，也结识了几个经验丰富的斫琴老师。我们正在和他们谈合作，邀请他们来指导我们斫琴，这样就可以持续不断地提供质优价低的古琴给大家，还可以邀请支持众筹项目的琴友前来，亲手监制一把自己的古琴！

Figure A2.
Parts of project description

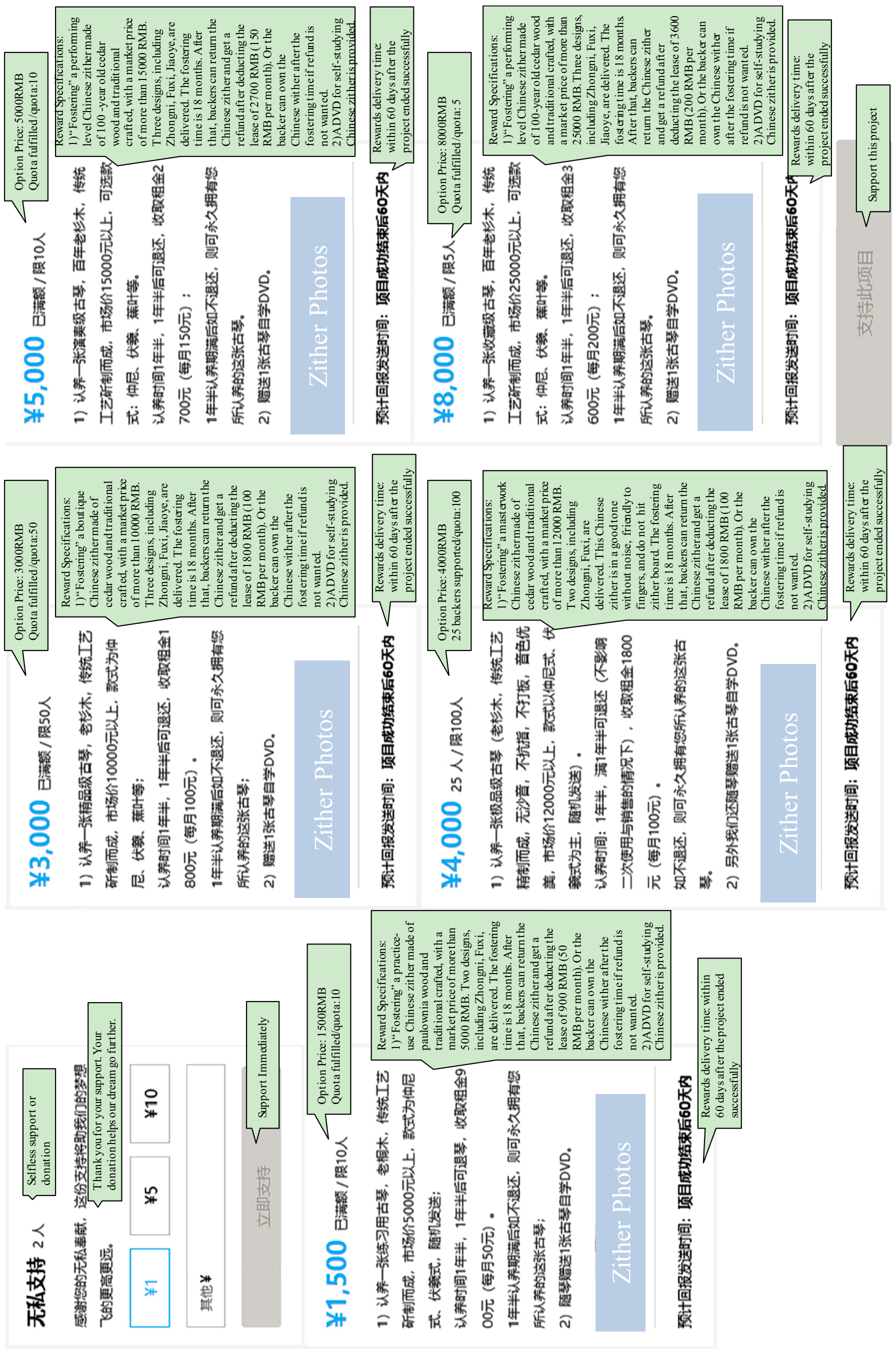


Figure A3.
Reward options

A screenshot of the project page is provided, which could be divided into three parts. On the top of the project page is the project overview, which includes project title, project initiator, featuring picture, real-time number of backers, real-time support amount, days left, target amount, fulfillment percentage, project tags, and buttons to share to social media as well as a button for instant supporting. In this project, the project had finished raising money. The total support amount was 355,002 RMB from 102 backers, which was 2,367% of the target amount 15,000 RMB.

The second part is the project description, which usually contains text, photos and videos, describing the project in detail. There are no set patterns for project initiators to describe their projects. A figure about parts of the project description is provided in the following.

The third part is the reward options. The reward options are on the right of the page. The options are vertically displayed, with the lowest price on the top and highest price on the bottom. To exhibit the reward options conveniently, we list the reward options in three columns rather than one column in Figure A3. In this case, the project provides five reward options as well as one donation option. The donation option is a feature from the donation-based crowdfunding, and it only solicit money but do not provide rewards, which is quite different from reward option. In Zhongchou.com, the donation button is platform-mandated after August 2015. In our paper, we only considered the effect from the number of reward options. More specifically, the backer could "foster" a practice-use Chinese zither made of paulownia wood if supporting 1,500 RMB, a boutique Chinese zither made of cedar wood if supporting 3,000 RMB, a masterwork Chinese zither made of cedar wood if supporting 4,000 RMB, a performing level Chinese zither made of 100-year old cedar wood if supporting 5,000 RMB, and a collection level Chinese zither made of 100-year old cedar wood if supporting 8,000 RMB. As we can see the prices are differentiated. We use the coefficient of variance to measure price differentiation, which is defined as the extent of how prices of one project are different from each other. It is calculated as: $\text{PriceDifferentiation} = \text{PriceMean}/\text{PriceStd}$. In this case, the price variation of this project is 0.507.

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