AMSE JOURNALS-AMSE IIETA publication-2017-Series: Advances A; Vol. 54; N°2; pp 346-359
Submitted Apr. 01, 2017; Revised Jun. 12, 2017; Accepted Jun. 28, 2017

The Effect of Risk Preference on Two Crowdsourcing Mechanisms

*Kunxiang Dong, ** Zongxiao Xie, ***Jie Zhen, ****Xiukun Zhao

* School of Management Science & Engineering, Shandong University of Finance and Economics, Jinan 250014, China (Corresponding author: dkxgood@163.com)
** China Financial Certification Authority, Beijing 100054, China (xiezongxiao@vip.163.com)
*** School of Business Planning, Chongqing Technology and Business University, Chongqing 400067, China (zhenjie886@163.com)
**** Business School, Tianjin University of Finance and Economics, Tianjin 300222, China (zhaoxiukun1986@163.com)

Abstract

The ubiquity of the Internet has promoted the importance and prevalence of crowdsourcing, an online distributed problem-solving and production model. Crowdsourcing harnesses the collective intelligence of a crowd of web users through an open-call format, and boasts immeasurable potential for government and non-profit applications. However, it is impossible to design an efficient crowdsourcing mechanism without the deep understanding of the optimal participation decisions made by sponsors and solvers. The previous studies on optimal participation decision in crowdsourcing have mainly focused on the impact of task factors, contest forms and individual factors with risk neutral solvers. In reality, however, the decision-making process of solvers is far from risk neutral, but directly affected by risk preference. In light of the problem, this paper explores the impact of rewards, the number of solvers and different risk preferences on decision-making in two crowdsourcing mechanisms: maximizing the total quality (TQ) and maximizing the best quality (BQ) of the task. The all-pay auction model and Stackelberg competition were built to obtain the optimal solutions of sponsors and solvers. Then, our model was validated based on the data extracted from taskcn.com. The results show that: (1) the solvers' expected utilities increase with rewards and risk preference, but decrease with the increase in the number of solvers; (2) the task quality obtained by sponsors, whether it is measured by the TQ or

the BQ, is directly proportional to rewards, the number of solvers and the risk preference. The data of taskcn.com significantly or partly supported the corollaries of the proposed model.

Key words

Crowdsourcing, All-pay action, Risk preference, Optimal decisions.

1. Introduction

Innovation is crucial to the survival of enterprises. However, the diffusion of innovation is often suppressed by first-mover advantages. With the development of information technology, especially the Web 2.0, it is increasingly easy to connect a large number of dispersed individuals. This gives birth to crowdsourcing, an efficient way for enterprise to achieve online innovation. Unlike the established ways of thinking, crowdsourcing innovation presents an array of new solutions (Blohm et al., 2013) and an efficient way to acquire new ideas (Mortara et al., 2013). For enterprises, online crowdsourcing manages to boost competitive power (Afuah and Tucci, 2012), innovation ability (Lüttgens et al., 2014) and performance (Dahl et al. 2014); For the government, online crowdsourcing promotes democratic consultation, transparent tendering, opinion solicitation and policy innovation (Wijnhoven et al., 2015). It is therefore not surprising that decision-makers of both the government and public and private organizations are competing to optimize the efficiency and effectiveness of the crowdsourcing innovation process.

Ranging from InnoCentive to Amazon's MTurk, numerous crowdsourcing websites have emerged in recent years and mobilized hundreds of thousands of potential innovators. Taking InnoCentive as an example, it is immensely popular among enterprises (e.g. Procter & Gamble, Nabisco and Avery Dennison) seeking innovative solutions to tackle their tackle problems and challenges. Nearly 200,000 engineers, scientists, inventors, businesspeople, and research organizations from more than 200 countries are registered in InnoCentive. The registered users have intense rivalries over business, chemistry, computer science, engineering, mathematics, design, and statistics. In China, more than 75% small and medium-sized enterprises have resorted to crowdsourcing for innovation and cheap labour cost. The booming crowdsourcing market is thronged with enterprises desperate for innovative solutions to their problems.

2. Literature Review

This section reviews the previous research on decision-making of sponsors and solvers. Overall, the existing studies mainly focus on the following two aspects.

(1) Extrinsic and intrinsic motivation of participations

The sponsors and solvers are motivated for different needs. Some scholars have explored the motivations of solvers. LaToza and van (2016) suggested that the main reasons for an enterprise to adopt crowdsourcing are overcoming internal constraints, accessing external innovation, collecting public wisdom and maintaining customer relationships. Ye and Atreyi (2015) found that an enterprise involved in crowdsourcing often seeks to reduce the cost, boost brand awareness, and acquire external technology.

As for the solvers, their motivations can be divided into extrinsic motivations and intrinsic motivations. The extrinsic motivations, as the primary driving factors of solution quality (Zheng et al., 2011), include rewards (Bayus, 2013; Harris and Wu, 2014), trust (Shen et al., 2014), self-ability, job opportunity, social motivation, learning and so on (Brabham, 2012). Intrinsic motivations, however, cover self-promotion, self-identity and emotional attachment (Bagozzi and Dholakia, 2002; Wang and Fesenmaier, 2004). Sun et al. (2012) discovered that the motivation is positively related to willingness, and is moderated by task complexity and self-efficacy.

(2) Incentive mechanism of participations

According to Terwiesch and Xu (2008), the effort of solvers decreases with the increase of number of solvers, but the diversity of solutions exhibits an increasing trend. The diversity of solutions may produce the best solution (Boudreau et al., 2011). However, the emergence of high quality solution may exclude other solvers from the contest (Liu et al., 2014), and drag down the overall quality of tasks. Naroditskiy et al. (2014) and Luo et al. (2016) believed that higher reward could encourage more solvers to attend the contest. Their view was refuted by Chen et al. (2010), who discovered no evidence on the positive correlation between solvers' effort and rewards. As a result, an enterprise always prefers constant reward over uncertain encouragement (Schöttner, 2008).

As stated above, the existing literature, focusing on the risk neutral scenario, has rarely considered the influence of risk preference of solvers on crowdsourcing decision. In real life, the risk preference plays an important role, especially under uncertain circumstances (Arrow, 1958). It is defined as the scale of preference orientation in taking risky actions (Antony, 2006). Moreover, the existing studies basically ignored the two objective mechanisms of sponsors in crowdsourcing contest, namely, maximizing the total quality (TQ) and maximizing the best quality (BQ). The former means the sponsors should pursue the best quality of all submitted solutions by encouraging all solvers through message promotion, labour service and multistage award tasks. The latter requires the sponsors to maximize the best solutions by encouraging the best solver via writing, translation, website development and logo/VI design. Owing to the varied optimal decisions of sponsors and solvers, there is marked difference in the objective, win probability and behaviour of solvers between the two mechanisms.

Through economic model and empirical study, this paper attempts to find the optimal decision of two crowdsourcing mechanisms considering the risk preference. The contributions of this research include: the discussion of how risk preference affects the optimal decisions, the provision of the indifference curve of two crowdsourcing mechanisms, and the testing of the proposed model with the data of taskcn.com. The remainder of this paper is organized as follows: Section 3 presents an all-pay auction model on the relationship between expected utility and quality of tasks; Section 4 derives the equilibrium of the Stackelberg competition and compares the two mechanisms; Section 5 verifies the effectiveness of the proposed model based on the data of taskcn.com; Section 6 analyses the findings and draws the conclusions.

3. Basic All-Pay Auction Model

Let us consider a one-shot game in which solvers select a contest and exert effort (at a cost depending on their skills), and in each contest the player with the best effort wins a prize. The specific settings of the game are as follows: the game involves N players in one crowdsourcing contest; each player i ($i = 1, 2...N$) has a vector of skills $v \in [0, \bar{v}]$, which is distributed continuously and independently according to a distribution function $F(v)$ and probability density function $f(v)$; each player submits a bid and pays his/her bid regardless of whether he/she wins or not, and only the highest bidder wins the cash reward M ; $F(v)$, N and M are public information. The action sequence of sponsors and solvers are shown in Figure 1.

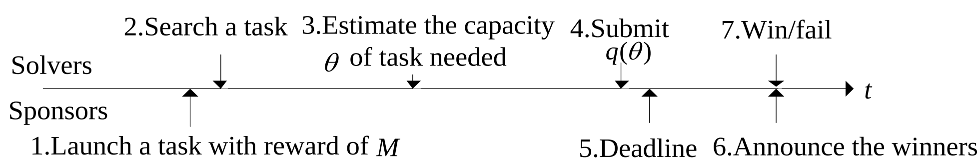

Fig.1. Action sequence of sponsors and solvers

If the capacity of task needed is estimated as $\theta \in [0, v]$, the submit quality of solver is $q(\theta)$. In this case, the Von Neumann–Morgenstern (VNM) utility function with risk preference of the winner is $(vM)^{\alpha} - q(\theta)^{\alpha}$, where $(vM)^{\alpha}$ is the utility generated by reward M . In the meantime, the loser has to pay the extra utility $-q(\theta)^{\alpha}$, where α is the degree of risk preference of solvers.

Otherwise, the solvers should pay an extra effort called fixed cost c, including the search cost and network fee. The expected utility $EU(\theta, v)$ is expressed as:

$$EU(\theta,v)=F^{N-1}(\theta)(vM)^{\alpha}-q^{\alpha}(\theta)-c \tag{1}$$

where F^{N-1} is the probability of winning. According to the Bayesian-Nash equilibrium (Di and Vojnovic, 2009), the best expected utility of solvers appears at $\theta = v$. Then, we have:

$$\frac{\partial EU(\theta,v)}{\partial\theta}=(N-1)F^{N-2}(\theta)f(\theta)(vM)^{\alpha}-\alpha q^{\alpha-1}(\theta)q'(\theta) \tag{2}$$

According to the boundary conditions, the following equation holds:

$$\begin{aligned} q(\theta) &= [(\theta M)^{\alpha}F^{N-1}(\theta)-\alpha M\int_0^{\theta}(xM)^{\alpha-1}F^{N-1}(x)dx]^{\frac{1}{\alpha}} \\ &= [\frac{(N-1)\theta^{N-1+\alpha}M^{\alpha}}{(N-1+\alpha)v^{N-1}}]^{\frac{1}{\alpha}} \end{aligned} \tag{3}$$

Thus, we have $q(\theta) < \theta MF^{\frac{N-1}{\alpha}}(v) \le vM$, indicating that the quality is smaller than the product of capability and rewards. By first-order derivation, we obtain the optimal competitive strategy of each solver $q(\theta)$, the winner's optimal strategy $q^{*}(\theta)$, as well as the TQ and the BQ of task:

$$q(\theta)=M[\frac{(N-1)\theta^{N-1+\alpha}}{(N-1+\alpha)v^{N-1}}]^{\frac{1}{\alpha}},\ q^{*}(\theta)=\max\arg\{q(\theta)\} \tag{4}$$

$$Q=N\int_0^{\theta}q(x)dx=\frac{\alpha NM}{(N-1+2\alpha)}[\frac{(N-1)\theta^{N-1+2\alpha}}{(N-1+\alpha)v^{N-1}}]^{\frac{1}{\alpha}},\ q=q^{*}(\theta) \tag{5}$$

Let $\Delta=\theta/v$ denotes the participation willingness, we have:

Corollary 1 Both the TQ and the BQ increase with participation willingness.

Based on equations (4) and (5), we have $q(\theta)=\theta M\Delta^{\frac{N-1}{\alpha}}(\frac{N-1}{N-1+\alpha})^{\frac{1}{\alpha}}$ and $dq/d\Delta>0$, which mean the BQ is proportional to participation willingness. Meanwhile, $Q(\theta)=\frac{\alpha NM\theta^2}{N-1+2\alpha}\Delta^{\frac{N-1}{\alpha}}(\frac{N-1}{N-1+\alpha})^{\frac{1}{\alpha}}$ and $dQ/d\Delta>0$, which mean the TQ is also proportional to participation willingness.

Corollary 2 Both the TQ and the BQ are positively correlated with capability.

The equations of the TQ and the BQ reveal that $Q(v)=\frac{\alpha v^2NM}{N-1+2\alpha}(\frac{N-1}{N-1+\alpha})^{\frac{1}{\alpha}}$ and $q(v)=vM(\frac{N-1}{N-1+\alpha})^{\frac{1}{\alpha}}$. This means the TQ and the BQ are respectively the quadratic function and linear function of capability.

Moreover, as $dq/dN>0$ and $dQ/dN>0$, it is possible to derive that:

Corollary 3 Both the TQ and the BQ are positively associated with the number of solvers.

According to above corollaries, we have $\lim_{N\to+\infty}Q(v)=\alpha v^2M$ and $\lim_{N\to+\infty}q(v)=vM$. Both the TQ and the BQ are positively related to rewards and capability of solvers. However, the TQ is also direct proportional to risk preference of solvers. If $v\to 0$, the capability of solvers declines, and the sponsors would acquire invalid solutions.

4. The Optimal Solutions of Two Mechanisms

This section discusses the optimal decisions of two mechanisms with sponsors as leaders and solvers as followers.

4.1 Mechanism 1: Maximizing the TQ

As a familiar format in crowdsourcing, the first mechanism demands solvers to spare no effort in solving the task so as to maximize the TQ of the solutions. In the Stackelberg competition, solvers determine how much effort should be paid according to the complexity and rewards of tasks and the number of competitors. Then, the Stackelberg competition of sponsors and solvers can be expressed as:

$$\begin{cases} \max\limits_{M,N} Q_0 = \dfrac{\alpha NM}{(N-1+2\alpha)}[\dfrac{(N-1)\theta^{N-1+2\alpha}}{(N-1+\alpha)v^{N-1}}]^{\frac{1}{\alpha}} \\ s.t. \quad \max\limits_{v} EU_0 = F^{N-1}(\theta)(vM)^{\alpha} - q^{\alpha}(\theta) - c \end{cases} \tag{6}$$

The above equation demonstrates that $dEU_0 / d\theta > 0$ and reveals that the optimal value occurs at $\theta = v$. Taking $\theta = v$ into Q, we have:

$$Q_0^* = \frac{\alpha v N^* M}{(N^*-1+2\alpha)}[\frac{(N^*-1)}{(N^*-1+\alpha)}]^{\frac{1}{\alpha}} \tag{7}$$

Thus, $Q'_M > 0$, that is, the quality increases with rewards.

Find $\ln Q_0^*$, the partial derivatives of M and N:

$$\frac{\partial^2 Q}{\partial M \partial N} = \frac{\partial^2 Q}{\partial N \partial M} = \frac{Q}{M}[\frac{1}{N} - \frac{1}{N-1+2\alpha} + \frac{1}{\alpha}(\frac{1}{N-1} - \frac{1}{N-1+\alpha})] \tag{8}$$

Then, the optimal number of solvers can be obtained by $\frac{1}{N} - \frac{1}{N-1+2\alpha} + \frac{1}{\alpha}(\frac{1}{N-1} - \frac{1}{N-1+\alpha}) = 0$. When $\alpha > 0.5$, the Q increases with the N, provided that the number of N is finite and denoted as $\bar{N}$.

$$N_0^* = \begin{cases} \dfrac{(1-2\alpha)(\alpha-1) + \sqrt{(1-2\alpha)(1-\alpha)(2\alpha^2 - 11\alpha + 1)}}{4a} & 0.5 \le \alpha < 1 \\ \bar{N} & 0 \le \alpha < 0.5, \alpha \ge 1 \end{cases} \tag{9}$$

Corollary 4 In pursuit of the maximum TQ, the expected utility and the TQ increase with the rewards.

Whereas $dEU_0^* / dM > 0$ and $dQ^* / dM > 0$, the expected utility and the TQ are both the increasing functions of rewards. Hence, it is wise for sponsors to raise the rewards and inspire the solvers.

Corollary 5 In pursuit of the maximum TQ, the expected utility is negatively related to the number of solvers, while the TQ is positively related to the number of solvers.

This corollary is evidenced by $dEU_0^* / dN < 0$ and $dQ^* / dN > 0$.

If there are an infinite number of solvers, we have $\lim_{N\to\infty} EU^*=0$. In this scenario, it is not wise for solvers to compete with many competitors at the same time. If there are a finite number of solvers, we have $\lim_{N\to\infty} Q^*=\alpha v\bar{M}$, revealing that sponsors could obtain a certain quality related to risk preference, capability and rewards.

Corollary 6 In pursuit of the maximum TQ, both expected utility and the TQ are proportional to risk preference of solvers.

Similar to the proof of Corollary 4, we have $dEU_0^* / d\alpha > 0$ and $dQ^* / d\alpha > 0$. The sponsors should encourage the solvers with high risk preference to maximize the TQ. In return, the solvers could obtain a higher expected utility.

4.2 Mechanism 2: Maximizing the BQ

As another familiar format in crowdsourcing, the second mechanism demands the best solver to spare no effort in solving the task so as to maximize the BQ of the solution. As mentioned above, in the Stackelberg competition, solvers determine how much effort should be paid according to the complexity and rewards of tasks and the number of competitors. Then, the Stackelberg competition of sponsors and solvers can be expressed as:

$$\begin{cases} \max\limits_{M,N} \ q(\theta) = M[\dfrac{(N-1)\theta^{N-1+\alpha}}{(N-1+\alpha)v^{N-1}}]^{\frac{1}{\alpha}} \\ s.t. \quad \max\limits_{\theta} EU = F^{N-1}(\theta)(vM)^{\alpha} - q^{\alpha}(\theta) - c \end{cases} \tag{10}$$

Solving equation (10) with the same method of Mechanism 1, we have the optimal effort of solvers $\theta^* = v$, expected utility $EU^* = (vM)^{\alpha}[\dfrac{\alpha}{\underline{N}-1+\alpha}]$, optimal reward of sponsors $M = \bar{M}$, optimal BQ $q^*(v) = vM[\dfrac{\underline{N}-1}{\underline{N}-1+\alpha}]^{\frac{1}{\alpha}}$, and the optimal number of solvers $N^* = \underline{N}$.

Similar to corollaries 4~6, we have the following corollaries for Mechanism 2:

Corollary 7 In pursuit of the maximum BQ, the expected utility and the BQ increase with the rewards.

Corollary 8 In pursuit of the maximum BQ, the expected utility is negatively related to the number of solvers, while the BQ is positively related to the number of solvers.

Corollary 9 In pursuit of the maximum BQ, both expected utility and BQ are proportional to risk preference of solvers.

To sum up, both the expected utility and quality of task increase with the rewards and risk preference. A large number of competitors facilitates sponsors in acquiring high quality, but frightens away solvers.

5. Empirical Analysis

Taskcn.com is one of the most popular online crowdsourcing platform in China, accounting for more than 56% of solvers across the country. In early 2015, there were over 58,000 tasks on the website, and 0.27 million solvers looking for rewards. The tasks are classified into 29 subareas in five major categories, namely design, network, writing, computer programming and multimedia.

5.1 Data Preparation and Evaluation

This subsection aims to test the above corollaries using the data collected from taskcn.com. The author obtained all the relevant variables in the task contests. The data were extracted by browsing through all the pages of each type of task. Overall, the dataset covers the information on 424 tasks registered between September 2014 and March 2015, and completed by the solvers who outcompeted others in the last three months. After removing the solvers with lower 4 credits, there were in total 159 valid records. The values of all potential variables in Section 2 were measured in Table 1 to test the corollaries and verify the validity of the model.

Tab.1. Variables and Data Item

Variables	Measurement method	Explanation
Risk preference	The frequency ratio of solution submission and winning in the last three months (Jiang et al. 2012)	The total times of solution submission and winning since solvers joined the platform were not adopted because only the most recent data can reflect the exact risk preference.
Number of solvers	The number of submitted solutions	The number of solvers was measured by the number of solutions because some solvers submitted two or three solutions.
TQ	The total credit of all the solutions	The quality of submitted solutions was measured by credit because solvers with higher credit boast higher solution quality (http://news.taskcn.com/gongzuozhefangwenxinde/4111.html.).
Average quality of task	The quotient of the TQ and the number of solvers	TQ/n
BQ	The highest credit among all the submitted solutions	

Expected utility	Success probability*(TQ-the credit of solver)	The function of expected utility.

Tab.2. Descriptive Analysis of Variables

Variables	Min.	Max.	Mean	SD
Reward	100	3000	525.77	504.12
Capacity of solvers	2	1770	297.25	423.45
Participation willingness	0	1617.67	93.29	237.97
Risk preference	1	24	9.60	5.10
Number of solvers	2	284	31.19	33.51
BQ	3	1775	1106.06	650.61
TQ	3	26321	50008.05	4799.01
Average quality of task	0.26	839.75	183.55	152.32
Expected utility	0	5604.33	655.56	795.56

Some records were removed from the dataset due to the absence of value of recentness, frequency and last performance fields. The descriptive analysis of variables is given in Table 2.

5.2 Data Analysis and Discussion

The correlation analysis was performed on IBM® SPSS® Statistics 20. With data collected from taskcn.com, all the nine corollaries were tested and the results are summarized in Table 3. The correlation values reflect the degree of correlation between dependent factors and independent factors. According to the overall results, the relationship between dependent and independent factors is statistically significant or partly significant.

To further discuss the effect of independent factors on dependent factors, the participation willingness, rewards and risk preference were divided into two dimensions by the mean of each factor: low dimension and high dimension. After removing some solvers who have zero credit (i.e. little contribution to task quality), the author obtained the number of effective solvers N^e .

Tab.3. Results of Corollaries Test

Variables	Average quality of tasks	TQ	BQ	Expected utility
Participation willingness	0.14	0.107^{ns} (C1)	0.182^{*} (C1)	-0.11
High	0.55^{**}	0.141	0.199	-0.22
Low	-0.74	-0.64	-0.31	0.046
Capability of solvers	0.41^{**}	0.10^{ns} (C2)	0.33^{**}(C2)	0.66^{**}

Rewards of task	0.16^{*}	0.67^{**}(C4)	0.41^{**}(C7)	0.14^{ns} (C4, C7)
High	0.06	0.48^{**}	0.26	-0.23
Low	0.25^{**}	0.59^{**}	0.53^{**}	0.25^{**}
Number of solvers	-0.14	0.42^{**}(C3, C5)	0.24^{**}(C3, C8)	0.07^{ns} (C5, C8)
Efficient number	0.07	0.49^{**}	0.36^{**}	-0.16^{*}
Risk preference	0.17^{**}	0.21^{**}(C6)	0.20^{**}(C9)	0.132^{ns} (C6, C9)
High	0.21	0.24	0.29^{*}	0.12
Low	0.22^{*}	0.10	0.11	0.24^{*}

Notes: a. Ci (i=1, 2, 3…7) indicates the corresponding corollaries of mathematical models' section; b. Pearson correlation r (*0.05, **0.01, ns: not significant).

As shown in Table 3, all corollaries were significantly or partly supported. This means participation willingness, capability of solvers, the number of solvers, rewards of task and risk preference have a significant positive effect on the TQ and the BQ. In the last column, the variables did not have significant effects on expected utility. Nevertheless, both low rewards and low risk preference exerted significant impacts on expected utility ($r=0.25$, $p<0.01$; $r=0.24$, $p<0.05$). The number of solvers exhibited insignificant effect on the expected utility, but the number of effective solvers had a significant negative correlation with expected utility ($r=-0.16$, $p<0.05$). Moreover, high participation willingness, high capacity and high number of effective solvers, low rewards and low risk preference were closely knitted with the average quality of tasks. Corollaries 1 and 2 were partly supported, which means the participation willingness and capacity of solvers had no significant effect on the TQ. In general, our model is valid based on the value of the data test.

Conclusion

As a focal point in recent research, crowdsourcing plays an increasingly important role in improving the innovation ability and operation efficiency of enterprises. In this paper, the author studied the influence of rewards, the number of solvers and risk preference in two crowdsourcing mechanisms. The all-pay auction model was adopted to capture the expected utilities and solutions quality, and the optimal solution of participations was acquired via Stackelberg competition models. The results show that rewards and risk preference had positive effect on the utilities and quality. However, the number of solvers exhibited greater impact on the quality improvement than utility expansion. This research is believed to complement the current research into crowdsourcing. The all-pay auction model with risk preference can be seen as an extension of the crowdsourcing contest model, allowing us to work with a much broader range of distributions.

Acknowledgements

We gratefully acknowledge the support of grants from the National Social Science Fund of China (Grant No. 17CGL019), the Natural Science Foundation of Shandong Province of China (Grant No. ZR2017BG010) and the Humanities and Social Sciences Program of Shandong Universities (Grant No. J17RB094).

References

1. I. Blohm, J.M. Leimeister, H. Krcmar, Crowdsourcing: How to benefit from (too) many great ideas, 2013, MIS Quarterly Executive, vol. 12, no. 4, pp. 199-211.
2. L. Mortara, S.J. Ford, M. Jaeger, Idea Competitions under scrutiny: Acquisition, intelligence or public relations mechanism, 2013, Technological Forecasting and Social Change, vol. 80, no. 8, pp. 1563-1578.
3. A. Afuah, C.L. Tucci, Crowdsourcing as a solution to distant search, 2008, Academy of Management Review, vol. 37, no. 3, pp. 355-375.
4. D. Lüttgens, P. Pollok, D. Antons, et al., Wisdom of the crowd and capabilities of a few: Internal success factors of crowdsourcing for innovation, 2014, Journal of Business Economics, vol. 84, no. 3, pp. 339-374.
5. D.W. Dahl, C. Fuchs, M. Schreier, Why and when consumers prefer products of user-driven firms: A social identification account, 2014, Management Science, vol. 61, no. 8, pp. 1978-1988.
6. F. Wijnhoven, M. Ehrenhard, J. Kuhn, Open government objectives and participation motivations, 2015, Government Information Quarterly, vol. 32, no. 1, pp. 30-42.
7. T.D. LaToza, H.A. van, Crowdsourcing in software engineering: Models, motivations, and challenges, 2016, IEEE software, vol. 33, no. 1, pp. 74-80.
8. H.J. Ye, A. Kankanhalli, Investigating the antecedents of organizational task crowdsourcing, 2015, Information & Management, vol. 52, no.1, pp. 98-110.
9. H. Zheng, D. Li, W. Hou, Task design, motivation, and participation in crowdsourcing contests, 2011, International Journal of Electronic Commerce, vol. 15, no. 4, pp. 57-88.
10. B.L. Bayus, Crowdsourcing new product ideas over time: An analysis of the Dell IdeaStorm community, 2013, Management science, vol. 59, no. 1, pp. 226-244.

11. C. Harris, C. Wu, Using tri-reference point theory to evaluate risk attitude and the effects of financial incentives in a gamified crowdsourcing task, 2014, Journal of Business Economics, vol. 84, no. 3, pp. 281-302.
12. X.L. Shen, M.K. Lee, M.K. Cheung, Exploring online social behavior in crowdsourcing communities: A relationship management perspective, 2014, Computers in Human Behavior, vol. 40, no. 1, pp. 144-151.
13. D.C. Brabham, Motivations for participation in a crowdsourcing application to improve public engagement in transit planning, 2012, Journal of Applied Communication Research, vol. 40, no. 3, pp. 307-328.
14. R.P. Bagozzi, U. M. Dholakia, Intentional social action in virtual communities, 2002, Journal of interactive marketing, vol. 16, no. 2, pp. 2-21.
15. Y. Wang, D.R. Fesenmaier, Towards understanding members' general participation in and active contribution to an online travel community, 2004, Tourism management, vol. 25, no. 6, pp. 709-722.
16. Y. Sun, Y. Fang, K.H. Lim, Understanding sustained participation in transactional virtual communities, 2012, Decision Support Systems, vol. 53, no. 1, pp. 12-22.
17. C. Terwiesch, Y. Xu, Innovation contests, open innovation, and multiagent problem solving, 2008, Management science, vol. 54, no. 9, pp. 1529-1543.
18. K.J. Boudreau, N. Lacetera, K.R. Lakhani, Incentives and problem uncertainty in innovation contests: An empirical analysis, 2011, Management science, vol. 57, no. 5, pp. 843-863.
19. T.X. Liu, J. Yang, L.A. Adamic, et al., Crowdsourcing with all-pay auctions: A field experiment on taskcn, 2014, Management Science, vol. 60, no. 8, pp. 2020-2037.
20. V. Naroditskiy, N.R. Jennings, P.H. Van, et al., Crowdsourcing contest dilemma, 2014, Journal of The Royal Society Interface, vol. 11, no. 99, pp. 1-8.
21. T. Luo, S.S. Kanhere, S.K. Das, et al., Incentive mechanism design for heterogeneous crowdsourcing using all-pay contests, 2016, IEEE Transactions on Mobile Computing, vol. 5, no. 9, pp. 2234-2246.
22. Y. Chen, T.H. Ho, Y.M. Kim, Knowledge market design: A field experiment at Google Answers, 2010, Journal of Public Economic Theory, vol. 12, no. 4, pp. 641-664.
23. A. Schöttner, Fixed-prize tournaments versus first-price auctions in innovation contests, 2008, Economic Theory, vol. 35, no. 1, pp. 57-71.
24. K.J. Arrow, Utilities, attitudes, choices: A review note, 1958, Econometrica: Journal of the Econometric Society, vol. 26, no. 1, pp. 1-23.

25. S. Antony, Z. Lin, B. Xu, Determinants of escrow service adoption in consumer-to-consumer online auction market: An experimental study, 2006, Decision Support Systems, vol. 42, no. 3, pp. 1889-1900.
26. P.D. Di, M. Vojnovic, Crowdsourcing and all-pay auctions, 2009, Proceedings of the 10th ACM Conference on Electronic commerce, 2009, New York, USA, pp. 119-128.
27. M. Jiang, W.L. McGill, Y. Cao, Participatory risk management: concept and illustration, 2012, International Journal of Social Computing and Cyber-Physical Systems, vol. 1, no. 3, pp. 268-285.