Crowdsourcing with All-pay Auctions:
a Field Experiment on Taskcn [*]

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Abstract

To understand the effects of incentives on crowdsourcing participation and submission quality, we conduct a field experiment on Taskcn, a large Chinese crowdsourcing site using all-pay auction mechanisms. We systematically vary the size of the reward, and the presence of a soft reserve in the form of the early entry of a high-quality submission. We find that a higher reward induces significantly more submissions and attracts higher quality users. However, unpredicted by theory, we find that high-quality users are significantly less likely to enter tasks where a high quality solution has already been submitted, resulting in lower quality in subsequent submissions in such soft reserve treatments.

Keywords: crowdsourcing, field experiment, all-pay auctions
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1 Introduction

The Internet has transformed how work is done, from allowing geographically dispersed workers to collaborate to enabling tasks to be globally crowdsourced through public solicitation (Howe 2006, Howe 2008, Kleeman, Voss and Rieder 2008). The term crowdsourcing typically refers to the open solicitation of effort on a well-defined task to a community (crowd) to obtain a submitted solution before a deadline. Crowdsoucing has become an increasingly popular choice for tasks, such as translation, programming, and website design. Due to the open nature of effort solicitation in crowdsourcing, it is important to understand how the incentives accompanying a task affect both participation and the quality of the output produced.

Historically, intrinsically interesting small tasks have been crowdsourced through voluntary contributions. A well-known example is the Audubon Society's Christmas Bird Count, the longest-running wildlife census. For 111 years, tens of thousands of birders and scientists have been recording the birds they encounter during the holiday season and contributing their data to the Audubon Society for scientific research. A more recent example is the ESP game, which uses an online coordination game to label large quantities of images on the Internet, generating high quality metadata which improve image search results while helping the visually impaired to navigate images on the Internet.[1]

In comparison, problems requiring substantial expertise and effort tend to be crowdsourced with monetary incentives. In such cases, a requester posts a problem and indicates a respective reward. In some crowdsourcing designs, individuals can claim the task and complete it without direct competition. In other designs, the task is open to an unlimited number of participants, and one or several of the submissions are chosen as winners. A recent example of the latter is the 2011 NASA Planetary Data System Idea Challenge on TopCoder.com, which calls for ideas for potential applications to enable exploration and analysis of the scientific data from NASA planetary missions. This challenge awarded five top submission prizes within two weeks of the start of the challenge.[2]

To obtain the best quality submissions, crowdsourcing sites experiment with different incentive mechanisms. For instance, some crowdsourcing designs allow an individual to claim a task as her own, thus becoming a monopolist provider of the solution. An example is the now defunct question-answering site, Google Answers, which employed 500 pre-selected researchers to answer consumer questions. Once a researcher chose a question, she locked it and became the sole provider of an official answer. If the answer was satisfactory, she received the reward. Similarly, Amazon's Mechanical Turk allows workers to choose small human intelligence tasks (HITs). Once a HIT is chosen, the worker becomes the sole provider of a solution. Field experiments conducted on Google Answers find that, while a higher reward increases the likelihood that a question is answered, it has no effect on answer quality (Chen, Ho and Kim 2010, Jeon, Kim and Chen 2010, Harper, Raban, Rafaeli and Konstan 2008). Similarly, on Amazon's Mechanical Turk, a higher reward is found to increase participation but to have no impact on quality (Mason and Watts 2009).

In contrast to Google Answers and Mechanical Turk, some crowdsourcing sites, such as Taskcn in China and TopCoder in the United States, introduce a competitive element in the form of con-

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[1] Source: `http://www.gwap.com/gwap/gamesPreview/espgame/`, retrieved on October 10, 2011.

[2] Source: `http://community.topcoder.com/tc?module=ProjectDetail&pj=30016974`, retrieved on September 16, 2011.

tests. In the simplest form of the contest, after a requester posts a task and reward, any user can submit a solution to the task. Each task may receive many submissions. Since every user who submits a solution expends effort regardless of whether or not she wins, this simplest form of contest mechanism is equivalent to a first-price all-pay auction, where everyone expends effort, but only the winner receives the reward. To our knowledge, no field experiment has been performed to understand the effect of the reward levels and reserve quality on either participation or submission quality in such a competitive setting.

In addition to allowing for competition, crowdsourcing sites experiment with other features of all-pay auctions. On Taskcn, for example, sequential all-pay auctions, where late entrants can observe the content of earlier submissions, used to be the only exchange mechanism. Recently, users were given the ability to password-protect their solutions.[3] Theoretically, if all users password-protect their solutions, a sequential all-pay auction is transformed into a simultaneous all-pay auction. On the other hand, if only a fraction of users password-protect their solutions, the contest becomes a hybrid sequential/simultaneous all-pay auction. In comparison, on TopCoder, every submission is sealed. Given the options available, an evaluation of the various design features in all-pay auction mechanisms can potentially inform and thus improve the design and outcome of crowdsourcing mechanisms.

To evaluate the effects of both reward size and early high-quality submission (i.e., a soft reserve) on overall participation and submission quality, we conduct a field experiment on Taskcn. In our experiment, we post translation and programming tasks on Taskcn. The tasks are of similar difficulty, but the reward is varied. In addition, for a subset of tasks, we submit a high quality solution early in the bidding period. Unlike earlier field experiments on Google Answers and Mechanical Turk, in the competitive setting of Taskcn, we find significant reward effects on participation and submission quality, which is consistent with our theoretical predictions. However, unpredicted by theory, we find that experienced users respond to our experimental treatments differently from inexperienced ones. Specifically, experienced users are more likely to enter auctions with a high reward than inexperienced users. Furthermore, they are less likely to enter an auction where a high quality solution is already posted. As a result, our reserve treatments result in significantly lower average submission quality than those without a reserve.

The rest of the paper is organized as follows. We first give an overview of Taskcn in Section 2. In Section 3, we review the crowdsourcing and all-pay auction literature. Section 4 presents a theoretical framework for sequential and simultaneous all-pay auctions. Section 5 presents the experimental design. Based on our theoretical framework and experimental design, we present our hypotheses in Section 6. Experimental results are presented in Section 7. Finally, in Section 8, we discuss our results and their design implications.

2   Taskcn: An Overview

Since the crowdsourcing site Taskcn (http://www.taskcn.com/) was founded in 2006, it has become one of the most popular online labor markets in China. On Taskcn, a requester first fills out an online request form with the task title, the reward amount(s), the closing date for

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[3]There are two methods of protecting solution content utilized on Taskcn. One is to use a pre-paid service provided by the site; the other is to submit the solution with password protection and send the password to the requester by email.

submissions, and the number of submissions that will be selected as winners. When the closing date is reached, the site sends a notice to the requester who posts the task, asking her to select the best solution(s) among all the submissions. The requester can also choose the best solution(s) before the closing date. Once the task is closed, the winner receives 80% of the reward and the site retains 20% of the reward as a transaction fee. As of August 24, 2010 Taskcn had accumulated 39,371 tasks, with rewards totaling 27,924,800 CNY (about 4.1 million USD).[4] Of the 2,871,391 registered users on Taskcn, 243,418 have won rewards.

To inform our field experiment, we crawled and analyzed the full set of tasks posted on Taskcn from its inception in 2006 to March 2009. As of the time of our crawl, tasks were divided into 15 categories, including requests for graphic, logo and web designs; translations; business names and slogan suggestions; and computer coding. Challenging tasks, such as those involving graphic design and website building, have the highest average rewards (graphic design: 385 CNY; web building: 460 CNY) as they require higher levels of expertise, whereas tasks asking for translations, or names and slogan suggestions offer lower average rewards (translation: 136 CNY; name/slogan: 170 CNY). In addition, most tasks (76.5%) select a single submission to win the reward.

Within the site, each ongoing task displays continually updated information on the number of users who have registered for the task and the number of submissions. Unless protected, each solution can be viewed by all users. Taskcn started a solution protection program, which hides the content of one's submission from other users. To protect a submission, a user pays a fee for the program.[5] Password-protected submissions are displayed to the requester ahead of other submissions. Instead of paying for solution protection, many users on Taskcn protect their solution content by submitting an encrypted solution and sending the password to the requester.

Once on the site, after reading task specifications and submitted solutions, a user can decide whether to register for a task and submit a solution before the closing date. A user can also view the number of credits accrued by previous submitters. The number of credits corresponds to the hundreds of CNY a user has won by competing in previous tasks, and may signal either expertise or likelihood of winning. Even after a user registers for a task, she may decide not to submit a solution. Furthermore, there is no filter to prevent low quality solutions.

Given Taskcn's design, it is of interest to understand how users respond to incentives induced by different design features. For example, does a higher reward induce more submissions and higher quality? Does the early entry of a high quality submission deter the submission of low quality solutions? What tasks are more likely to elicit password-protected solutions? Do experienced users respond to incentives differently from inexperienced users? We address each of these questions in our subsequent experimental design and data analysis.

3 Literature Review

Our research is closely related to two streams of literature: the empirical literature on crowdsourcing, and the theoretical and experimental literature on all-pay auctions. Thus, we discuss each area of research separately below.

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[4]The exchange rate between the US dollar and the Chinese yuan was 1 USD = 6.8 CNY in 2009 and 2010.

[5]The fee ranges from 90 CNY for three months to 300 CNY for a year.

3.1 The Crowdsourcing Literature

Spurred by the increasing number of both simple and complex tasks solicited and fulfilled online, research on crowdsourcing has emerged in several academic disciplines, including economics, sociology, and information and computer sciences. In this section, we focus on studies that specifically investigate incentive structures. In what follows, we organize the findings by the incentive structures provided by various crowdsourcing sites, in the order of monopoly, contest, and non-pecuniary incentive. A key question explored in this literature is what factors affect participation levels and overall solution quality.

We first examine the provider-as-a-monopolist incentive structure, where the solution provider becomes the sole provider for a request once she claims it. One example of such a site is Google Answers, which employed 500 researchers to provide answers to customer questions, each priced between $2 and $500. While Harper et al. (2008) find that a higher reward leads to significantly better answer quality on Google Answers, Chen et al. (2010) find no such reward effects. To reconcile these findings, Jeon et al. (2010) conduct a meta-analysis using data from both studies. Using the Heckman correction for selection bias (Heckman 1979), they find that, while a higher reward increases the likelihood that a question is answered, conditional on getting an answer, a higher reward has no effect on quality. In addition, they find that researcher reputation is the only significant predictor of answer quality. We refer the reader to Chen et al. (2010) for a comprehensive review of the literature related to incentive effects on answer quality in online question-answering communities.

With a similar monopolist incentive structure as Google Answers, the Amazon Mechanical Turk (MTurk) is designed to employ human labor to perform small human intelligence tasks (HITs) that computers are not yet good at, such as tagging images and describing products. Unlike Google Answers, these tasks are typically priced at less than a dollar per task. A field experiment conducted by Mason and Watts (2009) on MTurk finds that, while a higher reward leads to higher participation, it does not lead to better solution quality, consistent with the findings in Jeon et al. (2010). We conjecture that the absence of a reward effect on quality is due to the monopolist incentive structure, i.e., a lack of competition once a provider takes up a question or a task.

Compared to the monopolist incentive structure, a contest ensures competition after a provider takes up a task, where the competitiveness depends on the number of entrants as well as their expertise and efforts. The best-known crowdsourcing sites using contests include Taskcn and Top-Coder. However, to our knowledge, existing studies of these two sites use naturally occurring field data.

As described in Section 2, on Taskcn, a requester posts a task to the site, along with a designated monetary reward amount and a deadline for submission. Users then submit their solutions. At the deadline, the requester chooses the winner, who receives 80% of the reward while the site receives 20%. In a study using data crawled from Taskcn, Yang, Adamic and Ackerman (2008a) find that, while a higher reward is correlated with more views ($\rho = 0.64$), the correlation between reward and the number of submissions is lower ($\rho = 0.43$). Importantly, using human coders for a random sample of 157 tasks, the authors find a positive and significant correlation between reward size and the skill requirements for the corresponding task, indicating that reward size is *endogenously* related to task difficulty. Therefore, to investigate the causality between reward and contestant behavior, it is important to *exogenously* vary the reward levels while controlling for task difficulty, which we do in this paper by conducting a randomized field experiment. Building on the empirical

findings of Yang et al. (2008a), DiPalantino and Vojnovic (2009) construct a theoretical all-pay auction model for crowdsourcing (subsection 3.2). Using a subsample of Taskcn data, they find that participation rates are increasing with reward at a decreasing rate, consistent with their theoretical prediction. However, neither study addresses the issue of quality. Thus, our study contributes to the research on crowdsourcing by investigating both participation and solution quality using a randomized field experiment.

Another well-known contest-based crowdsourcing site, TopCoder.com, is the largest competitive software development community in the world. Unlike Taskcn where the sequential all-pay auction is the prevalent mechanism, TopCoder uses simultaneous all-pay auctions, where a contestant cannot observe the content of others' submissions before submitting her own solution, although both the identities and ratings of other entrants are known. Using historical data from the TopCoder website, Archak (2010) finds that reward is a significant determinant of solution quality. Furthermore, Archak finds that highly-rated contestants tend to sign up early in the registration phase to deter the entry of other contestants. In an empirical analysis of the effects of competition, Boudreau, Lacetera and Lakhani (forthcoming) find that, while the average solution quality decreases with a larger number of competitors for easier problems, greater competition increases solution quality for more challenging tasks.

In addition to monetary incentives, crowdsourcing sites may also use non-pecuniary incentives. The most prevalent non-pecuniary incentives are reputation systems. While a contestant on Taskcn earns one credit point for every 100 CNY she wins on the site, a contestant on TopCoder receives an average grade from three expert reviewers for each submission. On Google Answers, each requester rates the official answer to her question on a 1-5 star scale. Each answerer's overall rating is public information.

On other sites, including Yahoo! Answers (Adamic, Zhang, Bakshy and Ackerman 2008), Naver Knowledge-In (Nam, Adamic and Ackerman 2009), and Baidu Knows (Yang and Wei 2009), each asker selects the best answer for her question and each site provides a system of status levels, awarding higher status to more active and valued contributors. Another form of non-pecuniary incentive is virtual currency. On Yahoo! Answers, a fixed number of points are awarded to a given activity, such as answering a question. On Baidu Knows and Knowledge-In, a requester may transfer points to the provider of the best answer to her question. In a field experiment comparing answer quality across different Q&A sites, Harper et al. (2008) find that Google Answers generates answers of higher quality than sites relying exclusively on non-pecuniary incentives.

Compared to the studies reviewed above, our study represents the first randomized field experiment on an all-pay auction crowdsourcing site. By exogenously varying reward levels and the presence of a soft reserve, our method enables us to more precisely evaluate the reward and reserve effects on participation and solution quality, while preserving the realism of a natural field setting (Harrison and List 2004).

3.2 All-pay Auction Literature

As Taskcn uses all-pay auctions as its contest mechanism, we review the theoretical and experimental literature on all-pay auctions in this subsection. In the economics literature, the first-price all-pay auction is often used to model rent-seeking, R&D races, lobbying, and tournaments. While most of this literature focuses on simultaneous all-pay auctions where players submit their bids without knowing others' bids, there is also a body of literature investigating properties of sequen-

tial all-pay auctions. Table 1 summarizes the theoretical and experimental studies, organized by the timing of bids and the relevant information structures.

Table 1: All-Pay Auction Literature: Theoretical Studies and Laboratory Experiments

	Simultaneous All-Pay Auctions	
	Theory	Laboratory Experiments
Complete Information	Baye, Kovenock and de Vries (1996) Bertoletti (2010) Anderson, Goeree and Holt (1998)	Potters, de Vries and van Winden (1998) Davis and Reilly (1998) Gneezy and Smorodinsky (2006) Lugovskyy, Puzzello and Tucker (2010) Liu (2011)
Incomplete Information	Amann and Leininger (1996) Krishna and Morgan (1997) Fibich, Gavious and Sela (2006) DiPalantino and Vojnovic (2009)	Noussair and Silver (2006)
	Sequential All-Pay Auctions	
	Theory	Laboratory Experiments
Complete Info.	Konrad and Leininger (2007)	Liu (2011)
Incomplete Info.	Segev and Sela (2011)	

Within this area of research, Baye et al. (1996) provide a theoretical characterization of the mixed strategy Nash equilibrium for a simultaneous all-pay auction under complete information. Bertoletti (2010) extends this model to investigate the role of a reserve price and finds that a strict reserve price increases allocation efficiency. In an incomplete information setting, both Krishna and Morgan (1997) and Amann and Leininger (1996) characterize the symmetric Bayesian Nash equilibrium.[6] While the previous studies focus on a single auction, DiPalantino and Vojnovic (2009) investigate a multiple all-pay auction model, where contestants choose between tasks with different rewards. In particular, DiPalantino and Vojnovic (2009) show that a higher reward increases participation levels. However, they do not examine the effect of reward on submission quality.

A number of laboratory experiments test the predictions of simultaneous all-pay auction models (Table 1, right column). Under complete information, most studies find that players overbid relative to the risk neutral Nash equilibrium predictions in early rounds but learn to reduce their bids with experience (Davis and Reilly 1998, Gneezy and Smorodinsky 2006, Liu 2011). An exception to this finding is Potters et al. (1998), who find bidding behavior consistent with Nash equilibrium predictions.[7] Rent overdissipation as a result of overbidding can be (partially) explained by a logit equilibrium (Anderson et al. 1998). In comparison, in an incomplete information and independent private value environment, Noussair and Silver (2006) find that revenue exceeds the risk neutral

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[6]Krishna and Morgan's model assumes that everyone's value for the object is randomly drawn from the same distribution, whereas Amann and Leininger (1996) prove the existence and uniqueness of a Bayesian Nash equilibrium in a two-player incomplete information all-pay auction with an asymmetric value distribution.

[7]The combination of several design features might explain the results in Potters et al. (1998), including small group size ($n = 2$), stranger matching and more periods (30).

Bayesian Nash equilibrium prediction, due to aggressive bidding by players with high valuations and passive bidding by those with low valuations. Both overbidding and behavioral heterogeneity among different types of players are consistent with risk aversion (Fibich et al. 2006).

Compared to research on simultaneous all-pay auctions, fewer studies investigate sequential all-pay auctions. Relevant to our study, in a complete information sequential all-pay auction model with endogenous entry, Konrad and Leininger (2007) characterize the subgame perfect Nash equilibrium, where players with the lowest bidding cost enter late, while others randomize between entering early and late. Extending this work to an incomplete information sequential all-pay auction setting, Segev and Sela (2011) demonstrate that giving a head start to preceding players can improve contestant effort. In a laboratory test of the Konrad and Leininger (2007) model, Liu (2011) finds that players learn to enter late with experience in all treatments.

In addition to the above, there is also a growing literature comparing all-pay auctions with other mechanisms in the fundraising context, which has a public good component, differentiating it from our study. We refer the reader to Carpenter, Matthews and Schirm (2010) for a summary of this literature and the references therein.

Compared to the existing literature on all-pay auctions, we conduct a field experiment on Taskcn, where features of sequential and simultaneous all-pay auctions coexist. As such, our results have the potential to inform the design of all-pay auctions for crowdsourcing sites.

4   Theoretical Framework

In this section, we outline our theoretical framework to derive comparative statics results which will serve as the basis for our experimental design and hypotheses. In doing so, we follow the model in Segev and Sela (2011), and extend their results to incorporate the effects of a reward and a reserve price on bidding strategies in sequential and simultaneous all-pay auctions.

In our model, there is a single task to be crowdsourced through an all-pay auction. The reward for the task is $v \geq 1$. There are n users, each differing in ability. Let $a_i \geq 0$ be user i's ability, which is her private information. User abilities are i.i.d. draws from the interval [0,1] according to the cumulative distribution function, $F(x)$, which is common knowledge. Additional assumptions on $F(x)$ will be introduced in subsections 4.1 and 4.2 respectively. The user with the best quality solution wins the reward, while other users incur time and effort in preparing their solutions.

To examine the effects of a reserve quality, i.e., a threshold solution representing the minimum acceptable quality, on participation levels and submission quality, we include a reserve quality, $q_0 \geq 0$. In this case, user i wins a reward equal to v if and only if the quality of her submission is the highest among the submissions and is at least as high as the reserve, i.e., $q_i \geq \max\{q_j, q_0\}$, $\forall j \neq i$. For technical reasons, we assume that ties are broken in favor of the late entrant.[8] For user i, a submission of quality q_i costs q_i/a_i, indicating that it is less costly for a high ability user to submit the same quality solution than a low ability user. In what follows, we separately characterize the comparative statics results in the sequential and simultaneous all-pay auctions under incomplete information. All proofs and examples are relegated to Appendix A.

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[8]This is a technical assumption to derive strict subgame perfect equilibria instead of ϵ-equilibria.

4.1 Sequential All-pay Auctions under Incomplete Information

Without allowing for password protection of solutions, the competitive process on Taskcn approximates a sequential all-pay auction, where solutions are submitted sequentially and the best solution is selected as the winner. Following Segev and Sela (2011), we first characterize the subgame perfect equilibria of a sequential all-pay auction under incomplete information. For theoretical results presented in this subsection, we need the additional assumption that $F(x) = x^c$, $0 < c < 1$, as in Segev and Sela (2011).[9]

In a sequential auction, each of n users enters the auction sequentially. In period i where $1 \leq i \leq n$, user i submits a solution with quality, $q_i \geq 0$, after observing previous submissions. Using backward induction, we characterize the equilibrium bidding functions of users n through 1, to derive the following comparative statics.

Proposition 1 (Reward Effect on Participation Level). *In a sequential all-pay auction under incomplete information, a higher reward weakly increases the likelihood that user i submits a solution of positive quality.*

Proposition 1 indicates that we expect reward size to have a non-negative effect on user participation. Intuitively, a user's likelihood of participation *ex ante* depends on the reward size and the highest quality submissions before hers. When the reward size increases, the highest quality among earlier submissions also increases. With a zero reserve and risk neutrality, these two effects cancel each other. In comparison, with a positive reserve, the reward effect on participation dominates that from the increase of the highest quality among earlier submissions, resulting in a strict increase in a user's likelihood of participation.

A requester's satisfaction with the auction outcome typically depends not only on the quantity of submissions, but more importantly, on the quality.

Proposition 2 (Reward Effect on Expected Submission Quality). *In a sequential all-pay auction under incomplete information, a higher reward increases user i's expected submission quality.*

Proposition 2 indicates that we expect reward size to have a positive effect on the expected submission quality. In Appendix A, we present a two-player example (Example 1) with closed-form solutions for the quality and likelihood of submissions, as well as the average and highest quality.

We now examine the effect of a positive reserve on participation. The following proposition parallels the equivalent reserve price effect on participation in winner-pay auctions where a positive reserve price excludes bidders with low values (Krishna 2009).

Proposition 3 (Reserve Effect on Participation Level). *In a sequential all-pay auction under incomplete information, a higher reserve quality decreases the likelihood that a user submits a solution with positive quality.*

Intuitively, the higher the reserve quality, the less likely it is that a user with a low ability will participate in the auction. In Appendix A, we present Example 2, a continuation of Example 1, to demonstrate the relevant comparative statics with respect to reserve quality.

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[9]Due to the complexity of player i's winning function, closed-form bidding functions for the general ability distribution function have not been obtained (Segev and Sela 2011).

As we do not have a general solution for the optimal reserve quality, we present a numerical example to illustrate the effects of reserve quality on the expected highest and average quality. Figure 1 presents the expected highest quality (left panel) and average quality (right panel) as a function of the reserve when $F(x) = x^c$, $c = 0.5$, $v = 1$ and $n = 2$. In this example, the reserve quality which maximizes the expected highest quality is 0.47, whereas the one which maximizes the expected average quality is 0.43.
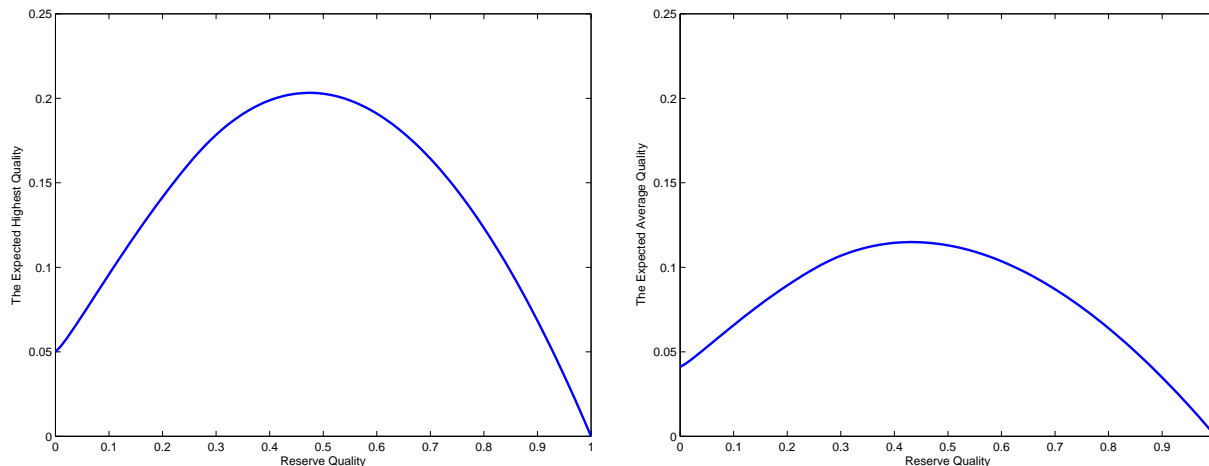

Figure 1: Effects of Reserve Quality on the Expected Highest and Average Quality: $c = 0.5$; $v = 1$; $n = 2$

The optimal reserve quality in this example is in the middle of the quality range. Intuitively, an appropriate reserve should exclude users with low abilities and thus increase the expected highest and average quality.

4.2 Simultaneous All-pay Auctions under Incomplete Information

In this subsection, we investigate the extreme case when all solutions to a task are submitted under password protection. In this scenario, the competitive process is approximated by a simultaneous all-pay auction, where users do not see others' solutions before submitting their own. The crowdsourcing process on TopCoder is an example of a simultaneous all-pay auction. We derive comparative statics for simultaneous all-pay auctions under incomplete information to examine the effects of reward size and reserve quality.

In a simultaneous all-pay auction, each user submits her solution without observing those of others. Each user's ability is again an i.i.d. draw from the cumulative distribution function $F(x)$ with support $[0, 1]$. To prove Propositions 4 through 6, we need the additional assumption that $H_i(x) = \prod_{j \neq i}^n F(x)$ is strictly concave and $H_i(0) = 0$. However, the assumption that $F(x) = x^c$ is not necessary for results in this subsection. We now state three propositions. The first two propositions examine the reward effects on participation level and submission quality, respectively.

Proposition 4 (Reward Effect on Participation Level)**.** *In a simultaneous all-pay auction under incomplete information, a higher reward weakly increases the likelihood that user i submits a solution of positive quality.*

Proposition 5 (Reward Effect on Expected Submission Quality). *In a simultaneous all-pay auction under incomplete information, a higher reward increases the expected submission quality.*

We now state the reserve effect on participation level.

Proposition 6 (Reserve Effect on Participation Level). *In a simultaneous all-pay auction under incomplete information, a higher reserve decreases participation.*

Unlike the sequential case, since every user in a simultaneous all-pay auction is symmetric *ex ante*, the reserve which maximizes the expected highest quality is the same as that which maximizes the expected average quality. We now present two numerical examples to illustrate the effects of reserve quality on the expected quality for each player in a simultaneous all-pay auction. The left panel in Figure 2 presents the expected quality for each player when $c = 0.2$, $v = 1$ and $n = 2$ and the optimal reserve quality is $q_0 = 0.4$. The right panel in Figure 2 presents the expected quality for each player when $c = 0.8$, $v = 1$ and $n = 2$ and the optimal reserve quality is $q_0 = 0$. The examples suggest that, in a simultaneous all-pay auction, the effect of a positive reserve on expected quality depends on the distribution of abilities. Thus, requesters might not always be better off by setting a positive reserve.
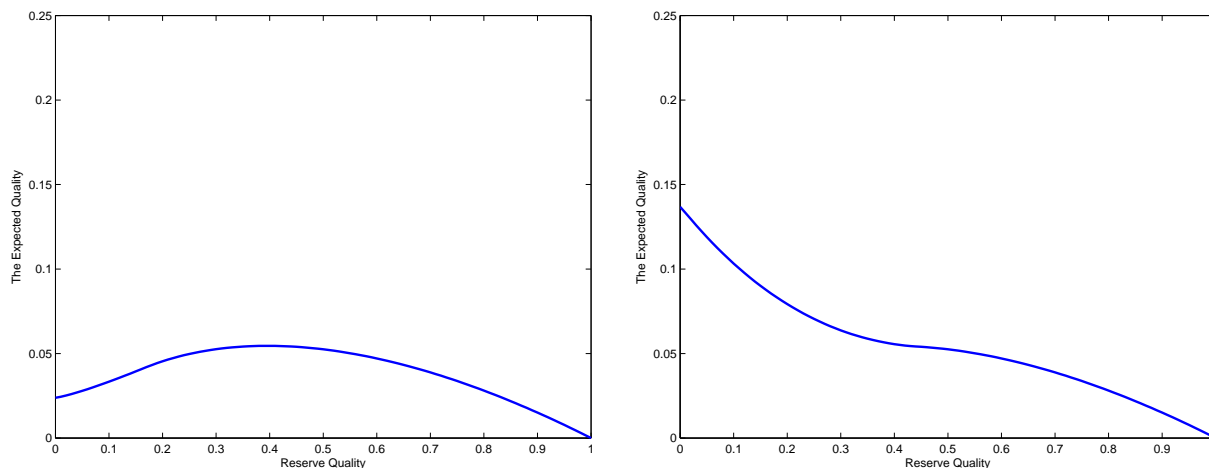

Figure 2: Effects of Reserve Quality on the Expected Quality: $c = 0.2$ (left), $c = 0.8$ (right); $v = 1$; $n = 2$

In this section, we separately characterize the reward and reserve effects on participation and submission quality under sequential and simultaneous all-pay auctions, respectively. We find that reward and reserve quality have similar effects on both participation and quality under each auction format. While these characterizations provide benchmarks for our experimental design and hypotheses, in reality, most all-pay auctions on Taskcn are hybrid sequential/simultaneous auctions, where participants endogenously determine whether to password protect their solutions. Two other features of the field not captured by our theoretical models are endogenous entry timing and the choice among multiple auctions, each of which is modeled by Konrad and Leininger (2007) and DiPalantino and Vojnovic (2009), respectively. A more realistic model which incorporates endogenous selection of the auction format, endogenous entry and choice among multiple auctions is left for future work. Nonetheless, our experiment provides a useful framework with which to study the effect of reward level and reserve presence on participation and submission quality.

5 Experimental Design

In this section, we outline our experimental design. We use a 2×3 factorial design to investigate the reward and reserve quality effects on user behavior on Taskcn. Specifically, we investigate whether tasks with a higher reward will attract more submissions and generate solutions of a higher quality. We are also interested in determining whether a high-quality solution posted early, playing the role of a soft reserve, will deter the entry of low quality solutions, especially if it is posted by a user with a history of winning on the site.

5.1 Task Selection: Translation and Programming

Of the task categories on Taskcn, we choose to use translation and programming tasks for our field experiment, as the nature of the respective solutions is fairly standard and objective.

Our translation tasks fall into two categories: personal statements collected from Chinese graduate students at the University of Michigan and company introductions downloaded from Chinese websites. We choose these two categories as they are challenging, each requiring a high level of language skills and effort compared to translating other types of documents, such as resumes. In Appendix B, we provide an example of a personal statement and an example of a company introduction, as well as a complete list of Taskcn IDs and URLs for all translation tasks used in our experiment.

For the programming tasks, we construct 28 programming problems, including 14 Javascript and 14 Perl tasks. None of our programming tasks is searchable and each has practical use. A complete list of the programming tasks is provided in Appendix B. One example of such a task reads: "Website needs a password security checking function. Show input characters as encoded dots when user types password. Generate an information bar to indicate the security level of the password, considering these factors: (1) length of the password; (2) mixture of numbers and characters; (3) mixture of upper and lower case letters; (4) mixture of other symbols. Please provide source code and html for testing." The functionality of such programming tasks can be assessed by qualified programmers.

Table 2: Summary Statistics about Tasks on Taskcn from 2006 to March 27, 2009

	Reward (in CNY)		# of Submissions	
	Mean	Median	Mean	Median
Translation	136	100	109	42
Programming	184	100	10	6

To prepare for our field experiment, we crawled all the tasks on Taskcn posted from its inception in 2006 to March 27, 2009. Table 2 presents summary statistics for these two types of tasks. While translation and programming tasks have the same median reward on the site, the former generate a higher median number of submissions, possibly due to the ability to submit a machine-generated solution.

5.2 Treatments

Our parameter choices are based on the summary statistics in Table 2. To investigate the reward effects, we choose two reward levels for our tasks, 100 CNY and 300 CNY, based on the following considerations. First, using the median reward for our low reward treatments guarantees a certain amount of participation. Second, the two reward levels have a monetarily salient difference.

As translation tasks posted by Taskcn users have a relatively large number of submissions on Taskcn (Table 2), we investigate whether the early entry of a high quality submission can influence participation, similar to the effect of a reserve price in an auction. Thus, for each reward level, we vary the reserve conditions, including No-Reserve, Reserve-without-Credit, and Reserve-with-Credit.[10] The two reserve conditions differ in whether the user posting the high quality solution has credits from previous wins. In the Reserve-without-Credit treatments, each early submission is posted by a user without a winning history on the site, whereas in the Reserve-with-Credit treatments, our submissions are posted by a user with four credits. To ensure the quality of the translations used in the reserve treatments, we ask a bilingual student (the owner of the personal statement when applicable) to provide the first round of English translations, and then a native English speaker to polish them.

Table 3: Number of Tasks by Experimental Treatment

		No-Reserve	Reserve-without-Credit	Reserve-with-Credit
Low-Reward	Programming (14)			
(100 CNY)	Translation (20)	Translation (20)	Translation (20)	
High-Reward	Programming (14)			
(300 CNY)	Translation (20)	Translation (20)	Translation (20)	

Table 3 summarizes our six treatments. The number in brackets indicates the number of tasks posted in a treatment. A total of 120 translation (28 programming) tasks are randomly assigned to six (two) treatments. Thus the full 2×3 factorial design is applied to translation tasks, while programming tasks are used to check for the robustness of any reward effects. We use a greater number of translation tasks in the field experiment in part because of the relative difficulty in generating unique, plausible, and comparable programming tasks.

5.3 Experimental Procedure

We posted 148 tasks on Taskcn between June 3 and 22, 2009, eight tasks per day (one translation and one programming task from each treatment) so as not to drastically increase the total number of tasks posted daily on the site.[11]

Each task was posted for seven days, with one reward per task. To avoid reputation effects from the requester side, we created a new user account for each task. After a task was posted, any

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[10]Recall that users earn 1 credit whenever they earn 100 CNY on the site. We created our own user account and obtained winning credits by winning tasks before the launch of our experiment.

[11]From January to March 2009, the average number of new tasks posted on the site per day is 12. Since each task is open between one week to a month, and all open tasks are listed together, users select from dozens to hundreds of tasks at a time.

user could participate and submit a solution within seven days. At the end of the seven-day period, we selected a winner for each task, excluding our reserve submissions.[12]

Table 4: Summary Statistics for User Credits

	Mean	Median	Min	Max	Standard Deviation
Translation	0.43	0	0	96	4
Programming	4	0	0	62	11

During our experiment, 948 users participated in the translation tasks, submitting a total of 3751 solutions, and 82 users participated in the programming tasks, submitting a total of 134 solutions. Table 4 presents the summary statistics of user credits among our participants. In addition to the number of submissions, participants also vary in their password protection behavior between these two types of tasks. We find that 8% of the translation and 53% of the programming solutions are submitted with password protection. The difference in the proportion of password-protected submissions is significant ($p < 0.01$, test of proportion, two-sided).

5.4 Rating Procedure

To determine submission quality, we recruited raters blind to the research hypotheses to evaluate each submission. All raters were graduate students from the University of Michigan. Our rating procedures follow the standard practice in content analysis (Krippendorff 2003). To evaluate the translation submissions, we proceeded in two stages. First, we recruited three bilingual Chinese students to independently judge whether a submission was machine-translated. If two of them agreed that a submission was machine-translated, we categorized it as a machine translation. Second, we recruited nine different bilingual Chinese students, whom we randomly assigned into three rating groups. For this stage, all valid translations plus one randomly-selected machine translation for each task were independently evaluated by three raters.[13] Raters for translation tasks each had scored above 600 on the TOEFL. To evaluate the programming submissions, we recruited three Chinese students, each with an undergraduate degree in computer science and several years of web programming experience. We conducted training and rating sessions for all raters. Raters within each rating group independently evaluated the same set of task-submission pairs. Details of the rating procedures and instructions can be found in Appendix C.

From October 2009 to February 2010, we conducted 45 rating sessions at the University of Michigan School of Information Laboratory. Each session lasted no more than two hours. Students were paid a flat fee of $15 per hour to compensate them for their time. We used intra-class correlation coefficients, ICC[3,3], to measure inter-rater reliability.

Table 5 presents the number of rating tasks and the inter-rater reliability for each rating group. The last two columns present the inter-rater reliability for each rating group. Good to excellent re-

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[12]We find that the average quality of the winning solutions (4.33) is not significantly different from that of our reserve submissions (4.36) based on the evaluation of raters blind to the research design and hypotheses ($p = 0.423$, one-sided paired t-test).

[13]Note that the machine translations were not marked in the second stage. Thus, this procedure provides an additional consistency check among raters.

Table 5: Rating Task Quantities and Inter-rater Reliabilities (ICC[3,3])

	Group	# Tasks	# Submissions	Task Difficulty	Submission Quality
Translation	1	43	265	0.62	0.90
	2	35	215	0.88	0.88
	3	42	284	0.72	0.68
Programming	1	28	108	0.55	0.77

liability is observed for all rating groups.[14] Additionally, machine translations are rated as having significantly lower quality than other valid translations in the second stage,[15] providing further evidence of rating consistency between the first- and second-stage raters. In our subsequent analysis, we use the median evaluation for the task difficulty and overall submission quality.[16]

6 Hypotheses

In this section, we describe our hypotheses comparing user behavior in different treatments based on the theoretical predictions outlined in Section 4. We are interested in two outcome measures: participation and submission quality.

Based on Propositions 1 and 4, we expect that a task with a higher reward will receive more participation.

Hypothesis 1 (Reward Effect on Participation). *A task with a high reward attracts more submissions than a task with a low reward.*

We now discuss the reserve effects on participation. Based on Propositions 3 and 6, we predict that the early entry of a high quality solution will decrease overall participation. Even though our reserve is not binding, we predict that users who cannot produce a translation with a higher quality will not participate. Thus, we expect to observe less participation in the reserve treatments compared to the no-reserve treatments. This effect should be stronger for the reserve-with-credit treatments.

Hypothesis 2 (Reserve Effect on Participation). *The number of submissions in the reserve treatments will be less than that in the no-reserve treatments.*

For submission quality, based on Propositions 2 and 5, we expect that a task with a higher reward will attract higher quality submissions.

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[14]In general, values above 0.75 represent excellent reliability, values between 0.40 and 0.75 represent fair to good reliability, and values below 0.40 represent poor reliability.

[15]On a 1-7 Likert scale, the average median quality of machine and valid translations is 2 and 5, respectively, significantly different from each other ($p < 0.01$, using ordered probit regressions with standard errors clustered at the task level).

[16]Task difficulty is measured by the median evaluation for questions 1(d) in translation and 1(b) in programming, whereas overall submission quality is measured by the median evaluation for questions 3 in translation and 2(d) in programming. See Appendix C for rating instructions.

Hypothesis 3 (Reward Effect on Submission Quality). *A task with a high reward attracts submissions of higher quality than a task with a low reward.*

Lastly, despite a lack of theoretical characterizations of the reserve effect on *expected* submission quality, we formulate a hypothesis based on *ex post* submission quality. We expect that the average submission quality in the reserve treatments will be higher than that in the no-reserve treatments, since only users who can generate a solution better than the reserve are expected to participate.

Hypothesis 4 (Reserve Effect on Submission Quality). *The average submission quality will be higher in the reserve treatments than in the no-reserve treatments.*

7 Results

Of the 120 translation and 28 programming tasks posted, we received submissions for every task. On average, each translation (programming) task received 1830 (1211) views, 46 (9) registrations and 31 (5) submissions. Although it might at first appear that participation is several times greater for translation tasks relative to programming tasks, most of the submissions for translation tasks are machine-generated. The average number of valid translations per task (5) is equal to that of solutions to programming tasks. Of the submissions received, 8% (53%) of the translation (resp. programming) solutions are password protected, making them hybrid sequential/simultaneous all-pay auctions.

A total of 948 (82) unique users participate in the translation (programming) tasks.[17] We categorize the participants based on their prior winning experience. We define *experienced users* as those who have won at least 100 CNY (with at least one reputation credit) prior to our experiment, whereas we define *inexperienced users* as those who have not. Table 6 reports the summary statistics of participant credits.[18] Specifically, we find that 4% (27%) of the participants in the translation (programming) tasks are experienced users.

Table 6: The Percentage of Each User Type in the Experiment

Task		Number of Users	Percentage	Median Credit	Mean Credit
Translation	Experienced Users	42	4	3	10
	Inexperienced Users	906	96	0	0
Programming	Experienced Users	22	27	5	10
	Inexperienced Users	60	73	0	0

Before analyzing our results, we first check that our randomization of tasks across treatments works. Pairwise Kolmogorov-Smirnov tests comparing task difficulty across treatments yield $p > 0.10$ for both translation and programming tasks, indicating that task difficulty is comparable across

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[17]We treat each unique ID as a unique user, as the reputation system on the site encourages users to keep a single identity across tasks.

[18]These summary statistics are computed based on field data from Taskcn from 2006 through June 2, 2009, the day before our experiment.

different treatments. In what follows, we evaluate the specific treatment effects on participation and submission quality.

We first examine whether different reward levels affect participation. Due to the existence of machine translations and solutions copied from others, we separately examine the effect of reward level on both the total number of translation submissions and that of valid translations. To qualify for a valid translation, a submission must be neither machine-translated nor copied from previous submissions. Similarly, we separate programming submissions into valid and invalid solutions. Of the 134 programming submissions, we find that 26 are invalid due to either incompleteness or copying from previous submissions. In both types of tasks, valid solutions involve a certain amount of effort in the preparation process, while invalid ones involve minimum effort. In our separate analyses, we find no significant difference between the reserve-with-credit and reserve-without-credit treatments in their effect on either participation or submission quality (participation: $p > 0.10$, two-sample t-tests; quality: $p > 0.10$, ordered probit regressions with standard errors clustered at the task level). Therefore, in subsequent analyses, we pool the two treatments together as a single reserve treatment.
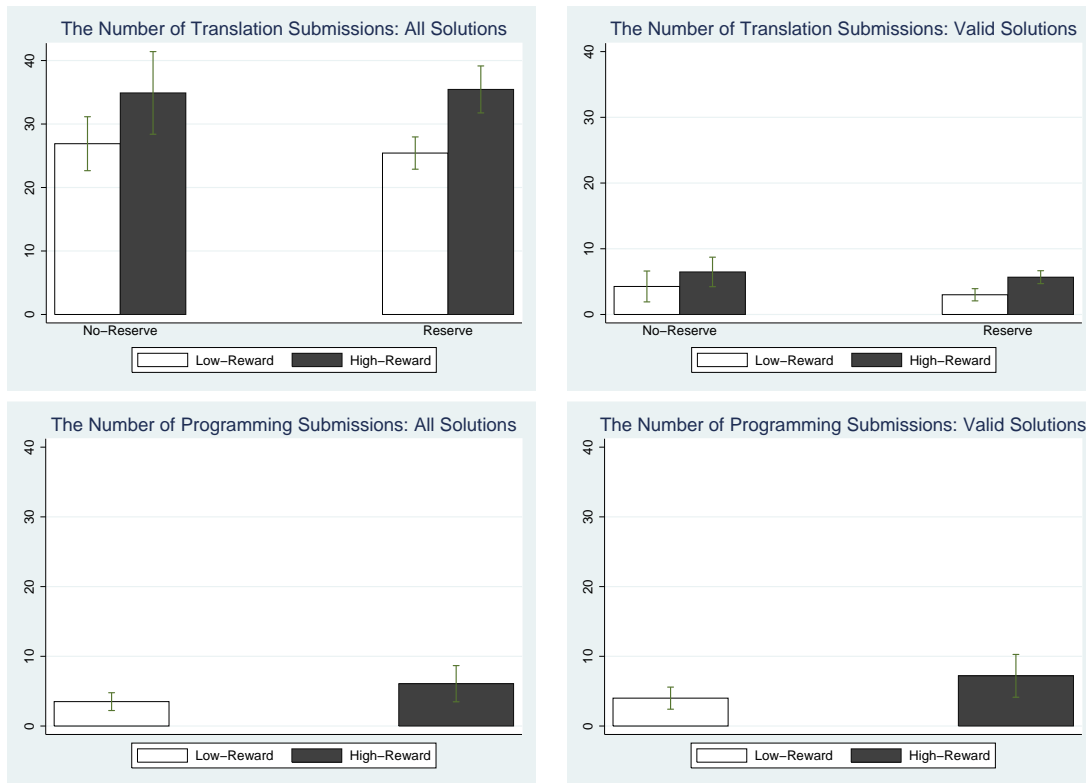
Figure 3: Reward Effect on Participation Level

Figure 3 presents the reward effect on participation in both the translation (top panel) and programming tasks (bottom panel). For each type of task, we present the participation data for all submissions and valid submissions separately. The average number of submissions and standard errors for the high- and low-reward treatments are presented in each graph. We summarize the results below.

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Result 1 (Reward Effect on Participation). *Translation (programming) tasks in the high-reward treatments receive significantly more submissions compared to those in the low-reward treatments.*

Support. *Table 7 presents the summary statistics and treatment effects for both the translation and programming tasks. Specifically, we find that the average number of translation submissions per task is significantly higher in the high-reward than in the low-reward treatments (no-reserve: $p = 0.019$; reserve: $p < 0.01$, one-sided two-sample t-tests). Furthermore, this difference is (weakly) significant for the subset of valid translations (no-reserve: $p = 0.081$; reserve: $p < 0.01$, one-sided two-sample t-tests). For programming tasks, one-sided permutation tests yield $p = 0.037$ for all submissions and $p = 0.031$ for valid submissions. Note that non-parametric tests are used for programming tasks due to the small number of tasks in each treatment.*

Table 7: Treatment Effects on the Average Number of Submissions Per Task

All Solutions	Translation			Programming	
	No-Reserve	Reserve	*Reserve Effect*		All
High-Reward	35	35	$p = 0.436$	High-Reward	6
Low-Reward	27	25	$p = 0.260$	Low-Reward	4
Reward Effect	$p = 0.019$	$p = 0.000$		*Reward Effect*	$p = 0.037$
Valid Solutions	Translation			Programming	
	No-Reserve	Reserve	*Reserve Effect*		All
High-Reward	6	6	$p = 0.251$	High-Reward	7
Low-Reward	4	3	$p = 0.153$	Low-Reward	4
Reward Effect	$p = 0.081$	$p = 0.000$		*Reward Effect*	$p = 0.031$

By Result 1, we reject the null hypothesis in favor of Hypothesis 1, that a higher reward induces more submissions. This result is consistent with our theoretical predictions in Propositions 1 and 4, as well as empirical findings on Taskcn (DiPalantino and Vojnovic 2009).

We now analyze the reserve effects on participation. Recall that Proposition 3 (6) predicts fewer submissions in the reserve treatments than in the no-reserve treatments in sequential (simultaneous) all-pay auctions. Interestingly, we find no difference in the number of submissions between the reserve and no-reserve treatments (Table 7, column 4). Thus, we fail to reject the null hypothesis in favor of Hypothesis 2.

Summarizing all treatments, Table 8 reports OLS regression analysis to enable a comparison of the relative effectiveness of the different treatments on participation in translation tasks. The dependent variables are the number of submissions for all solutions (1) and valid solutions (2). Independent variables include the following variables (with omitted variables in parentheses): high-reward (low-reward), reserve (no-reserve), and task difficulty. From Table 8, we see that the coefficient of the high-reward dummy is positive and significant at the 1% level in both (1) and (2), indicating a robust reward effect on participation when we control for other factors. Specifically, from low-reward to high-reward tasks, the average number of submissions increases by 10 (3) for all (valid) solutions. The coefficient for task difficulty is negative and significant, indicating that more difficult tasks receive fewer submissions.

In addition to participation, we are also interested in factors affecting the quality of valid submissions. Two outcome measures are used to evaluate quality: the quality of all valid submissions

Table 8: OLS: Determinants of the Number of Submissions in Translation Tasks

Dependent Variable	# of Submissions (All)	# of Submissions (Valid)
	(1)	(2)
High-Reward	9.749***	2.626***
	(1.859)	(0.671)
Reserve	-1.511	-1.328*
	(1.996)	(0.717)
Task Difficulty	-2.995***	-0.840**
	(0.970)	(0.349)
Constant	38.90***	7.681***
	(4.505)	(1.626)
Observations	120	112
R^2	0.232	0.167

Notes:

1. Standard errors are in parentheses.
2. Significant at: * 10%; ** 5%; *** 1%.

and the quality of the best solution for each task. For some tasks, e.g. programming, only the quality of the best solution may matter. However, in modularizeable tasks, the requester might care about the average quality of the submitted solutions. One example is translation, where different translations may be combined at the sentence or paragraph level. Thus, we examine the reward effect on both the average and the highest submission quality.

Table 9 presents four ordered probit specifications, which investigate factors affecting submission quality for all valid translations and best translations. The dependent variables are the quality of valid translations (specifications 1 and 2) and that of best translations (specifications 3 and 4), while the independent variables include the following variables (with omitted variables in parentheses): high reward (low reward), reserve (no-reserve), and task difficulty. Specifications (1) and (3) report pooled models with standard errors clustered at the task level. We find that the coefficient of the high-reward dummy is positive and significant in (1), indicating a reward effect on the average submission quality, whereas the same coefficient is positive but insignificant in (3), indicating the absence of a reward effect on the quality of the best translations. In comparison, the coefficient of the reserve dummy is negative and significant in both specifications, indicating a negative reserve effect on quality when we control for other factors. The coefficient of task difficulty is positive and significant at the 5% level in (1), indicating that solutions to more difficult tasks are more likely to get higher quality ratings. As 43% (38%) of the users who submit a valid (best) solution participate in more than one task, we then report fixed effects models in specifications (2) and (4) to investigate whether the estimation in the pooled model is driven by the within-user variation in the submission quality over tasks. In the fixed effects model, we fail to find significant reward effect on submission quality within each user. However, the reserve dummy remains negative and significant, indicating that each user produces lower submission quality for tasks with a reserve compared to those without a reserve. We summarize the results below.

Result 2 (Reward Effect on Submission Quality). *The average quality of valid translations is significantly higher in the high-reward treatments than in the low-reward treatments. Furthermore,*

Table 9: Ordered Probit: Determinants of Submission Quality for Valid and Best Translations

Dependent Variable	Quality of Valid Translations		Quality of Best Translations	
	(1)	(2)	(3)	(4)
High Reward	0.312**	-0.004	0.277	-0.152
	(0.146)	(0.187)	(0.255)	(0.418)
Reserve	-0.596***	-1.127***	-0.962***	-1.665***
	(0.153)	(0.200)	(0.263)	(0.393)
Task Difficulty	0.138**	0.169**	0.200	0.295*
	(0.0645)	(0.074)	(0.142)	(0.172)
User Fixed Effects	No	Yes	No	Yes
Observations	533	533	178	178
R^2	0.038	0.387	0.087	0.465

Notes:
1. Robust standard errors in parentheses are clustered at the task level in (1) and (3).
2. Significant at: * 10%; ** 5%; *** 1%.

this effect is not driven by within-user variations over different reward levels.

Support. *Table 9 presents four ordered probit specifications with and without user fixed effects. The high-reward dummy is positive in (1) and (2), significant in (1) but not in (2).*

By Result 2, we reject the null hypothesis in favor of Hypothesis 3 that a task with a high reward attracts submissions of higher quality than a task with a low reward. Furthermore, our fixed effects model indicates that, among users who participate in multiple tasks, there is no evidence that a user produces submissions of higher quality for high-reward tasks than those for low-reward tasks. In comparison, we find that, while programming tasks in the high-reward treatment attract higher average quality submissions than those in the low-reward treatment, this difference is not statistically significant (average quality of valid solutions: 3.88 vs. 3.75, $p = 0.220$, using ordered probit with standard errors clustered at the task level; average quality of best solutions: 5.00 vs. 4.78, $p = 0.380$, using one-sided permutation tests). Using similar analysis, we find that the reserve effects on quality is significant whether user fixed effects are controlled for, indicating that within-user variation accounts for part of the reserve effects on quality.

Result 3 (Reserve Effect on Submission Quality). *The quality of valid and best translations is significantly lower in the reserve treatments than in the no-reserve treatments. This effect is partially driven by within-user variation over the presence of a reserve.*

Support. *Table 9 presents four ordered probit specifications with and without user fixed effects. The reserve dummy is negative and significant in all four specifications.*

Note that Result 3 contradicts Hypothesis 4. While a fully rational user should submit a solution only when its quality exceeds that of any previous submissions including the reserve, our participants do not always follow this simple rule. Our subsequent analysis suggests that the quality of valid translations submitted after the reserve are lower because the reserve deters the entry of

more experienced users. By extension, experienced users differ from inexperienced ones in their ability to recognize high quality submissions.

The crucial factor which drives both Results 2 and 3 is user entry decisions. We now analyze user entry decisions by type, computed from two perspectives: user quality exhibited within our experiment, and their winning history prior to the start of our experiment.

We first investigate entry decisions using user quality computed within our experiment. We hypothesize that one possibility which might have led to the significant results in the pooled model is that tasks with a high reward (reserve) are more likely to attract (deter) high-quality users. To test this hypothesis, we construct a two-stage model.[19] In the first stage, we regress submission quality of each solution on the user dummies. Consequently, the estimated coefficient for user i, $\hat{\mu}_i$, approximates her user quality compared to that of the omitted user. This measure of user quality might be determined by various factors, including user ability, effort and reputation. We then construct a new statistic, $\bar{\hat{\mu}}_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \hat{\mu}_t$, representing the average user quality per task, and regress $\bar{\hat{\mu}}_t$ on the reward size of each task, the reserve dummy and the task difficulty.

Table 10: OLS: Determinants of the User Quality in Translation Tasks

Dependent Variable	Average User Quality Among Valid Solutions	Average User Quality Among Best Solutions
	(1)	(2)
High-Reward	0.757***	1.490**
	(0.219)	(0.623)
Reserve	-0.519**	-0.879
	(0.224)	(0.585)
Task Difficulty	-0.005	-0.125
	(0.118)	(0.433)
Constant	-1.742***	-0.106
	(0.428)	(1.303)
Observations	112	103
R^2	0.145	0.085

Notes:

1.Robust standard errors are in parentheses

2.Significant at: * 10%; ** 5%; *** 1%.

Table 10 reports two OLS specifications investigating determinants of average user quality among valid (specification 1) and best (specification 2) translation submissions. In specification (1), we find that the coefficient of the high-reward dummy is positive and significant, indicating that a high-reward task attracts higher-quality users. In comparison, the coefficient of the reserve dummy is negative and significant, indicating that average user quality in a task with a reserve is lower. For best solutions (2), the coefficient of the high-reward dummy is positive and significant, indicating that, among users who provide best solutions, average user quality is significantly higher for a high-reward task compared to that for a low-reward task. In comparison, the coefficient of the reserve dummy is negative but insignificant ($p = 0.136$, two-sided).

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[19]We thank Jeff Smith for suggesting this approach.

Having analyzed entry decisions based on user quality exhibited within our experiment, we proceed to investigate entry decisions using user winning history prior to the start of our experiment. To do so, we first compute the median user credit per task. Considering all valid solutions for a task, we find that the average median user credit is higher in the high-reward treatment than that in the low-reward treatment. This difference is significant in the no-reserve treatments.

Result 4 (Reward Effect on Entry)**.** *Average user quality among valid and best translations is significantly higher in the high-reward than in the low-reward treatments. Furthermore, the average median user credit is significantly higher in the high-reward-no-reserve than in the low-reward-no-reserve treatment.*

Support. *Table 10 reports two OLS specifications investigating determinants of average user quality in translation tasks. The coefficient for the high-reward dummy is positive and significant in both specifications. Using user credit prior to our experiment, we find that, in the no-reserve treatments, the average median user credit is 0.45 in the high-reward treatment, and 0.05 in the low-reward treatment. A one-sided two-sample t-test rejects the null hypothesis in favor of the alternative hypothesis that the average median credit is higher in the high-reward treatment ($p = 0.048$). For the reserve treatments, the relationship holds but is not significant (0.14 vs. 0.09, $p = 0.290$, one-sided two-sample t-tests). In comparison, among all valid programming solutions for each task, again, the relationship holds but is not significant (2.09 vs. 1.34, $p = 0.196$, one-sided permutation tests).*

Using similar analysis, we now summarize the reserve effects on entry decisions, using user quality observed during our experiment (Table 10) and user credits accumulated prior to our experiment. Using user credit history as an indication of their type, we find that, among all valid solutions for a high-reward task, the average median user credit is weakly lower in the reserve treatment.

Result 5 (Reserve Effect on Entry)**.** *Average user quality among valid translations is significantly lower in the reserve than in the no-reserve treatments. Furthermore, the average median user credit is weakly lower in the reserve-high-reward than in the no-reserve-high-reward treatments.*

Support. *Table 10 reports two OLS specifications investigating determinants of user quality in translation tasks. The coefficient for the reserve dummy is negative and significant in specification (1). Using user credit prior to our experiment, we find that, in the high-reward treatment, the average median user credit is 0.14 in the reserve treatment and 0.45 in the no-reserve treatment. A one-sided two-sample t-test rejects the null hypothesis in favor of the alternative hypothesis that the average median credit is lower in the reserve treatment at the 10% level ($p = 0.097$). For the low-reward treatments, the comparison between the reserve and no-reserve treatments is not significant (0.05 vs. 0.09, p=0.323, one-sided two-sample t-tests).*

Overall, Result 5 indicates that the early entry of a high quality translation is more likely to deter high-quality (experienced) users compared to low-quality (inexperienced) users. The differential entry response to the presence of a high quality reserve partially explains our finding that the reserve has a negative effect on subsequent submission quality (Result 3).

Lastly, to test the theoretical predictions on entry timing in sequential all-pay auctions from Konrad and Leininger (2007), we investigate factors influencing submission time. Using naturally occurring field data on Taskcn, Yang, Adamic and Ackerman (2008b) find a positive correlation

between reward size and later submission. A possible explanation is that users, especially experienced ones, strategically wait to submit solutions for high reward tasks. An alternative explanation is that higher rewards are offered for more difficult tasks, which require more time to complete. As reward level is endogenously determined in naturally occurring field data but exogenously determined in our experiment, we are able to separate the effects of reward size and task difficulty on submission timing.

Table 11: Determinants of Submission Time

Dependent Variable	Submission Time (All)		Submission Time (Valid)	
	(1)	(2)	(3)	(4)
High-Reward	0.200***	0.133***	0.466**	0.305
	(0.045)	-0.045	(0.232)	(0.208)
Valid Solution		1.236***		
		(0.109)		
Reserve		-0.032		-0.0261
		(0.049)		(0.195)
Task Difficulty		0.013		0.216**
		(0.024)		(0.092)
Experienced Users		0.074		0.754***
		(0.102)		(0.280)
Constant	0.571***	0.402***	1.457***	0.632
	(0.032)	(0.115)	(0.200)	(0.415)
Observations	3,515	3,515	485	485
R^2	0.004	0.088	0.011	0.040

Notes:
1. Standard errors in parentheses are clustered at the task level.
2. Significant at: * 10%; ** 5%; *** 1%.

In Table 11, we report four OLS specifications to investigate factors affecting submission time for all (specifications 1 and 2) and valid translations (specifications 3 and 4). To replicate results from Yang et al. (2008b), specifications (1) and (3) include the high-reward dummy as the only independent variable. In comparison, specifications (2) and (4) include the following additional independent variables (with omitted variables in parentheses): reserve (no reserve), task difficulty, and experienced users (inexperienced users). When other variables are not controlled for, we replicate the finding in Yang et al. (2008b) that a high reward has a positive and significant effect on submission time. However, this significance disappears for valid solutions after controlling for task difficulty and user experience. We summarize these results below.

Result 6 (Submission Time). *For valid translations, experienced users submit their translations significantly later than do inexperienced ones, controlling for task difficulty.*

Support. *In specification (4) of Table 11, the coefficient of the experienced user dummy is positive and significant at the 1% level, indicating that experienced users submit their solutions later than others. On average, experienced users submit their solutions 0.754 days later than inexperienced ones do.*

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Among all solutions, we find that those for a high-reward task are submitted 0.13 days later. Furthermore, a valid translation is submitted 1.236 days later than a machine-translation. Restricting our analysis to valid submissions, translations for a high-reward task are still submitted significantly later than those for a low-reward task. After controlling for task difficulty, however, we find that experienced users submit their solutions 0.754 days later than inexperienced users do, while the reward effect on submission time is no longer significant. Furthermore, the task difficulty coefficient is positive and significant, indicating that users take 0.216 days longer to submit a valid solution for each additional level of difficulty (on a 1-7 Likert scale).

In summary, we find significant reward effects on participation levels and submission quality. Furthermore, a higher reward also attracts higher quality (more experienced) users, indicating that a monetary incentive is effective in inducing more submissions and better solutions. Interestingly, while the early entry of a high quality solution does not significantly affect the number of submissions, we find that solution quality dramatically decreases with the presence of a reserve, as it deters the entry of high quality (experienced) users. In addition to their entry decisions, experienced users also submit their solutions later than inexperienced users do, controlling for task difficulty.

8 Discussion

As crowdsourcing has become an increasingly important problem-solving method, utilized by individuals, non-profit and for-profit organizations alike, evaluating the behavioral response of various design features will help improve the performance of crowdsourcing institutions and increase user satisfaction. In this study, we examine the effect of different design features of a crowdsourcing site on participation levels, submission quality and user entry decisions. Conducting a field experiment on Taskcn, a nascent online labor market, we find that a higher reward induces more participation and higher submission quality. By controlling for the existence of a reserve in the form of a high quality early submission, we find that a reserve lowers subsequent submission quality, as it preferentially deters the entry of experienced users. Experienced users also distinguish themselves from inexperienced ones by being more likely to select higher reward tasks over lower reward ones, and by submitting their solutions later.

Through our field experiment, we are able to observe interesting patterns that likely would not have emerged had the experiment been conducted in a lab setting. The most surprising finding of our experiment is that the entry decisions of high quality (experienced) users drive the reward and reserve effects on submission quality. A higher reward attracts more experienced users, while a high quality reserve deters them. This finding not only informs the design of crowdsourcing institutions, but also provides useful feedback to theory (Samuelson 2005). While most existing theoretical models of all-pay auctions ignore entry decisions, the model with endogenous entry (DiPalantino and Vojnovic 2009) treats every user as fully rational, which cannot explain our reserve effects on quality.[20] Our results suggest that a more accurate theory for predicting behavior in the field should incorporate behavior of both naive and sophisticated types, such as an extension of the cognitive hierarchy model (Camerer, Ho and Chong 2004) to the all-pay auction domain.

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[20]Morgan, Orzen and Sefton (2010) presents a theoretical model with endogenous participation in the Tullock contest, which differs from an all-pay auction.

The second is the way the site actually provides users with the power to transform a sequential all-pay auction into a simultaneous all-pay auction, by allowing users to hide solutions from other participants. We find that valid solution providers are more likely to protect their solutions compared to those who provide machine-generated translations (10% vs. 2%, $p < 0.01$, one-sided test of proportions), suggesting that the result of true effort is more likely to be protected from being copied by others. Again, the endogenous choice of auction format has not been evaluated theoretically. Our study provides the first empirical evaluations of such mechanisms, which might inform future theoretical research.

Lastly, we find that the majority of translations submitted are machine translations, which require very little effort on the part of the participants but increase the screening effort of requesters. This finding reveals the need for an entry barrier or censoring mechanism if a site wants to provide a better user experience for requesters. In addition, while a reserve in the form of an early high quality solution deters the entry of high quality (experienced) users in the experiment, it does not deter low-quality submissions, which indicates the need for additional incentives to attract high quality and deter low-quality users. One possible way to encourage earlier entry by experts is a tie-breaking rule favoring an earlier entry, as has been tested and confirmed in a lab setting by Liu (2011).

Finally, a feature of the Taskcn site we did not explore in this study is the option of designating multiple winners as opposed to a single winner for a task. Using multiple rewards to induce greater effort than a single reward is well-modeled (Moldovanu and Sela 2001) and examined in laboratory experiments (Muller and Schotter 2010). However, to our knowledge, there has not yet been a field experiment investigating the effect of allowing multiple winners on submission behavior. This can be a natural extension of our present work.

Appendix A: Proofs and Examples

Recall that Propositions 1 through 3 require the assumption that the ability distribution function is from the family, $F(x) = x^c$, where $0 < c < 1$.

Proof of Proposition 1: In what follows, we will consider two cases, the case with a zero reserve, and one with a positive reserve.

Case 1: Zero Reserve. We first derive the equilibrium bidding function for each user, when the reserve is zero, i.e., $q_0 = 0$.

Using backward induction, we expect that user n will win the auction if the quality of her solution is higher than or equal to the best quality among all previous submissions, which is $\max\{q_j(a_j)\}_{j<n}$, and if her ability is sufficiently high, $a_n \geq \frac{1}{v}\max\{q_j(a_j)\}_{j<n}$. If her ability is not high enough, i.e., $a_n < \frac{1}{v}\max\{q_j(a_j)\}_{j<n}$, her benefit from winning (v) is less than her bidding cost, thus she should bid zero. Therefore, the equilibrium bidding function of the last user, n, is given by:

$$q_n(a_n) = \begin{cases} 0 & \text{if } 0 \leq a_n < \frac{1}{v}\max\{q_j(a_j)\}_{j<n}, \\ \max\{q_j(a_j)\}_{j<n} & \text{if } \frac{1}{v}\max\{q_j(a_j)\}_{j<n} \leq a_n \leq 1. \end{cases} \tag{1}$$

Next, we derive the equilibrium bidding function for user i, where $i = 2, \ldots, n-1$. We do so by solving the following constrained optimization problem. Applying the Revelation Principle, user i with ability a_i will choose to behave as a user with ability s who maximizes her expected payoff:

$$\begin{aligned} \max_s \quad & \{v \prod_{j=i+1}^n F_j(q_j = 0) - \frac{q_i(s)}{a_i}\} \\ \text{s.t.} \quad & q_i(s) \geq \max\{q_j(a_j)\}_{j<i}. \end{aligned} \tag{2}$$

As $F(x) = x^c$, the probability that user i wins the auction conditional on her submitting a solution with quality at least as high as the best previous submission becomes:

$$\prod_{j=i+1}^n F_j(q_j = 0) = \left[\frac{q_i(s)}{v}\right]^{c(1-c)^{(n-(i+1))}} \left[\frac{q_i(s)}{v}\right]^{c(1-c)^{(n-(i+2))}} \ldots \left[\frac{q_i(s)}{v}\right]^{c} = \left[\frac{q_i(s)}{v}\right]^{1-(1-c)^{n-i}}.$$

When the constraint is not binding, the first-order condition is then:

$$v[1 - (1-c)^{n-i}]\left[\frac{q_i(s)}{v}\right]^{-(1-c)^{n-i}} \frac{q_i'(s)}{v} - \frac{q_i'(s)}{a_i} = 0.$$

Assuming the interior part of the equilibrium bidding function is strictly monotone, i.e., $q_i'(s) > 0$, the first-order condition becomes:

$$[1 - (1-c)^{n-i}]\left[\frac{q_i(s)}{v}\right]^{-(1-c)^{n-i}} - \frac{1}{a_i} = 0. \tag{3}$$

Therefore, the interior solution is $q_i(a_i) = v[a_i(1 - (1-c)^{n-i})]^{\frac{1}{(1-c)^{n-i}}}$. Let $d_i \equiv (1-c)^{n-i}$. Thus, we can rewrite the interior solution as:

$$q_i(a_i) = v[a_i(1 - d_i)]^{\frac{1}{d_i}}. \tag{4}$$

The second-order condition is then:

$$q_i''(s)\left[(1 - d_i)\left(\frac{q_i(s)}{v}\right)^{-d_i} - \frac{1}{a_i}\right] + \frac{(q_i'(s))^2}{v}\left\{-d_i\,(1 - d_i)\left[\frac{q_i(s)}{v}\right]^{-d_i-1}\right\}$$

$$= -\frac{(q_i'(s))^2}{v}\left\{d_i\,(1 - d_i)\left[\frac{q_i(s)}{v}\right]^{-d_i-1}\right\}, \text{ as the first term is zero by Equation (3),}$$

$$< 0.$$

To characterize the equilibrium bidding function, we define two boundaries as:

$$\overleftarrow{a}_i = \left[\frac{\max\{q_j(a_j)\}_{j<i}}{v}\right]^{d_i}, \text{ and } \overrightarrow{a}_i = \frac{1}{1 - d_i}\left[\frac{\max\{q_j(a_j)\}_{j<i}}{v}\right]^{d_i}.$$

These boundaries partition the support of abilities into three ranges:

1. When $0 \le a_i < \overleftarrow{a}_i$, the expected payoff from submitting a positive bid is negative. Thus, the user should submit a zero bid.

2. When $\overleftarrow{a}_i \le a_i < \overrightarrow{a}_i$, as $\max\{q_j(a_j)\}_{j<i} > v[(1 - d_i)a_i]^{\frac{1}{d_i}}$, bidding $\max\{q_j(a_j)\}_{j<i}$ dominates $v[(1 - d_i)a_i]^{\frac{1}{d_i}}$. Therefore, the constraint is binding, and we obtain a corner solution.

3. When $\overrightarrow{a}_i \le a_i \le 1$, Equation (4) is the interior solution of the constrained optimization problem (2) while the constraint is not binding.

Summarizing the above analysis, we characterize the equilibrium bidding function for user $i \in \{2, \cdots, n-1\}$ as follows:

$$q_i(a_i) = \begin{cases} 0 & \text{if } 0 \le a_i < \overleftarrow{a}_i, \\ \max\{q_j(a_j)\}_{j<i} & \text{if } \overleftarrow{a}_i \le a_i < \overrightarrow{a}_i, \\ v[a_i(1 - d_i)]^{\frac{1}{d_i}} & \text{if } \overrightarrow{a}_i \le a_i \le 1. \end{cases} \tag{5}$$

Note that when $\max\{q_j(a_j)\}_{j<i} \ge v(1 - d_i)^{\frac{1}{d_i}}$, the third range of Equation (5) does not exist.

Lastly, user 1's bidding function is $q_1(a_1) = v[a_1(1 - d_1)]^{\frac{1}{d_1}}$, where $0 \le a_1 \le 1$.

Now we derive the comparative statics of the reward effect on participation. Let $P_i(q_i = 0)$ be the probability that user i bids zero. For user $i > 1$, the probability of bidding zero depends on $\overleftarrow{a}_i$. Since $\max\{q_j(a_j)\}_{j<i} = \max\{v[a_j(1 - d_j)]^{\frac{1}{d_j}}\}_{j<i} = v\max\{[a_j(1 - d_j)]^{\frac{1}{d_j}}\}_{j<i}$, we obtain $\overleftarrow{a}_i = \max\{[(1 - d_j)a_j]^{\frac{d_i}{d_j}}\}_{j<i}$, which is independent of the reward level, v. In addition, for user 1, $q_1(a_1) > 0, \forall a_1 > 0$, and $a_1 = 0$ is a measure zero event. Therefore, $P_1(q_1 = 0) = 0$. In summary,

with a zero reserve, the probability of participation for any user i, $1 - P_i(q_i = 0)$, is independent of v.

Case 2: Positive Reserve. We now consider the positive reserve case, i.e., $q_0 > 0$.

As in Case 1, we first characterize the equilibrium bidding function of the last user, n, in the following two scenarios:

1. If the maximum bid from previous users does not exceed the reserve, i.e., $\max\{q_j(a_j)\}_{j<n} \leq q_0$, the only constraint for user n is the reserve, q_0. Thus, user n's bidding function becomes:

$$q_n(a_n) = \begin{cases} 0 & \text{if } 0 \leq a_n < \frac{q_0}{v}, \\ q_0 & \text{if } \frac{q_0}{v} \leq a_n \leq 1. \end{cases} \tag{6}$$

   When $a_n < \frac{q_0}{v}$, the expected payoff from submitting a positive bid is negative. Thus, she should bid zero. When $a_n \geq \frac{q_0}{v}$, as $\max\{q_j(a_j)\}_{j<n} \leq q_0$, the optimal bidding strategy for user n is to bid q_0. Consequently, she wins the auction.

2. If the maximum bid from previous users exceeds the reserve, i.e., $\max\{q_j(a_j)\}_{j<n} > q_0$, user n's bidding function is characterized by Equation (1).

For user i, $i = 2, ..n - 1$, her equilibrium bidding function, $q_i(a_i)$, is the solution to the optimization problem (2), with the additional constraint, $q_i(s) \geq q_0$. It is separately characterized in the following two scenarios:

1. If the maximum bid from previous users does not exceed the reserve, i.e., $\max\{q_j(a_j)\}_{j<i} \leq q_0$, the equilibrium bidding function is characterized by

$$q_i(a_i) = \begin{cases} 0 & \text{if } 0 \leq a_i < \overleftarrow{a}_i, \\ q_0 & \text{if } \overleftarrow{a}_i \leq a_i < \overrightarrow{a}_i, \\ v[a_i(1-d_i)]^{\frac{1}{d_i}} & \text{if } \overrightarrow{a}_i \leq a_i \leq 1, \end{cases} \tag{7}$$

   where the boundaries are defined as $\overleftarrow{a}_i(v, q_0) = (\frac{q_0}{v})^{d_i}$ and $\overrightarrow{a}_i(v, q_0) = \frac{1}{1-d_i}(\frac{q_0}{v})^{d_i}$.

2. If the maximum bid from previous users exceeds the reserve, i.e., $\max\{q_j(a_j)\}_{j<i} > q_0$, the equilibrium bidding function is characterized by Equation (5).

Lastly, user 1's equilibrium bidding function is characterized by Equation (7) with $i = 1$.

To characterize user i's *ex ante* likelihood of submitting a solution with positive quality, e.g., $P_i(q_i > 0)$, we first compute her probability of bidding zero, $P_i(q_i = 0)$.

Define $q_i^* \equiv [a_i(1-d_i)]^{\frac{1}{d_i}}$ as user i's bid in the third range of her equilibrium bidding function when $v = 1$.

First, when $i = 1$, the probability of bidding 0 is $F(\overleftarrow{a}_1(v, q_0)) = F\left((\frac{q_0}{v})^{d_1}\right)$ and $\{\partial F\left((\frac{q_0}{v})^{d_1}\right)\}/\{\partial v\} = (-cd_1)v^{-cd_1-1}q_0^{cd_1} < 0$.

Next, for user $i > 1$, we define a sequence of conditional probabilities, $N_i(v, q_0)^{(j)}$, where $1 \leq j < i$, as follows:

$$N_i(v, q_0)^{(1)} = P_i(q_i = 0 | q_1 \leq q_0),$$

$$\ldots$$

$$N_i(v, q_0)^{(j)} = P_i(q_i = 0 | q_1, \ldots, q_j \leq q_0),$$

$$\ldots$$

$$N_i(v, q_0)^{(i-1)} = P_i(q_i = 0 | q_{j<i} \leq q_0) = F\left(\overleftarrow{a}_i(v, q_0)\right) = F\left((\frac{q_0}{v})^{d_i}\right).$$

Therefore, $N_i(v, q_0)^{(j)} = P_i(q_i = 0 | q_1, \ldots, q_j \leq q_0)$ is the conditional probability for user i to bid 0 when none of the first j users' bids exceeds the reserve. In particular, $N_i(v, q_0)^{(i-1)}$ is the conditional probability for user i to bid 0 when none of the previous bids exceeds the reserve, which is equivalent to user i being the first active user in the new sequence with $n - i + 1$ users.

Define another sequence of conditional probabilities for each user $i > 1$, $O_i(a_j)$, where $1 \leq j < i$, as follows:

$$O_i(a_1) = P_i(q_i = 0 | q_1 = vq_1^*),$$

$$O_i(a_2) = P_i(q_i = 0 | q_1 \leq q_0, q_2 = vq_2^*),$$

$$\ldots$$

$$O_i(a_j) = P_i(q_i = 0 | q_1, \ldots, q_{j-1} \leq q_0, q_j = vq_j^*),$$

$$\ldots$$

$$O_i(a_{i-1}) = P_i(q_i = 0 | q_1, \ldots, q_{i-2} \leq q_0, q_{i-1} = vq_{i-1}^*) = F\left(\overleftarrow{a}_i(q_{i-1}^*)\right) = F\left((q_{i-1}^*)^{d_i}\right).$$

Therefore, $O_i(a_j) = P_i(q_i = 0 | q_1, \ldots, q_{j-1} \leq q_0, q_j = vq_j^*)$ is the conditional probability for user i to bid 0 when none of the bids before user j exceeds the reserve, $q_1, \ldots, q_{j-1} \leq q_0$, and user j's bid is the equilibrium bid in the third range of her equilibrium bidding function, vq_j^*.

Moreover, $\forall 1 < j \leq i$, we characterize the conditional probability for user i to bid 0 when none of the first $j - 1$ bids exceeds the reserve as:

$$N_i(v, q_0)^{(j-1)} = \int_0^{\overrightarrow{a}_j(v,q_0)} N_i(v, q_0)^{(j)} f(a_j) da_j + \int_{\overrightarrow{a}_j(v,q_0)}^1 O_i(a_j) f(a_j) da_j. \tag{8}$$

The first term is the conditional probability for user i to bid 0 with a random variable $q_j \leq q_0$, $P_i(q_i = 0, q_j \leq q_0 | q_1, \ldots, q_{j-1} \leq q_0)$. The second term is the conditional probability for user

i to bid 0 with a random variable $q_j = vq_j^* \geq q_0$, $P_i(q_i = 0, q_j = vq_j^* | q_1, \ldots, q_{j-1} \leq q_0)$. Differentiating Equation (8) with respect to v and using the Leibniz integral rule, we obtain:

$$
\begin{aligned}
\frac{\partial N_i(v, q_0)^{(j-1)}}{\partial v} &= \frac{\partial \overrightarrow{a}_j(v, q_0)}{\partial v} N_i(v, q_0)^{(j)} f\left(\overrightarrow{a}_j(v, q_0)\right) + \int_0^{\overrightarrow{a}_j(v, q_0)} \frac{\partial N_i(v, q_0)^{(j)}}{\partial v} f(a_j) da_j \\
&\quad - \frac{\partial \overrightarrow{a}_j(v, q_0)}{\partial v} O_i\left(\overrightarrow{a}_j(v, q_0)\right) f\left(\overrightarrow{a}_j(v, q_0)\right).
\end{aligned}
$$

By continuity of the equilibrium bidding function at $\overrightarrow{a}_j(v, q_0)$, we have $N_i(v, q_0)^{(j)} = O_i\left(\overrightarrow{a}_j(v, q_0)\right)$. Therefore, the first and third terms on the RHS cancel each other, which simplifies the RHS:

$$
\begin{aligned}
\frac{\partial N_i(v, q_0)^{(j-1)}}{\partial v} &= \int_0^{\overrightarrow{a}_j(v, q_0)} \frac{\partial N_i(v, q_0)^{(j)}}{\partial v} f(a_j) da_j \\
&= \frac{\partial N_i(v, q_0)^{(j)}}{\partial v} F\left(\overrightarrow{a}_j(v, q_0)\right),
\end{aligned}
\tag{9}
$$

as $\{\partial N_i(v, q_0)^{(j)}\} / \{\partial v\}$ is independent of a_j.

Therefore, the probability of bidding 0 for user i, $P_i(q_i = 0)$, can be rewritten as:

$$
P_i(q_i = 0) = \int_0^{\overrightarrow{a}_1(v, q_0)} N_i(v, q_0)^{(1)} f(a_1) da_1 + \int_{\overrightarrow{a}_1(v, q_0)}^1 O_i(a_1) f(a_1) da_1.
$$

Expanding $N_i(v, q_0)^{(1)}$ and $O_i(a_1)$, we have:

$$
\begin{aligned}
N_i(v, q_0)^{(1)} &= P_i(q_i = 0 | q_1 \leq q_0) \\
&= \int_0^{\overrightarrow{a}_2(v, q_0)} \int_0^{\overrightarrow{a}_3(v, q_0)} \cdots \int_0^{\overrightarrow{a}_{i-1}(v, q_0)} \left[\int_0^{\overleftarrow{a}_i(v, q_0)} f(a_i) da_i\right] \ldots f(a_2) da_2 \\
&\quad + \int_0^{\overrightarrow{a}_2(v, q_0)} \int_0^{\overrightarrow{a}_3(v, q_0)} \cdots \int_{\overrightarrow{a}_{i-1}(v, q_0)}^1 \left[\int_0^{\overleftarrow{a}_i(q_{i-1}^*)} f(a_i) da_i\right] \ldots f(a_2) da_2 \\
&\quad + \ldots \\
&\quad + \int_{\overrightarrow{a}_2(v, q_0)}^1 \int_{\overrightarrow{a}_3(q_2^*)}^1 \cdots \int_{\overrightarrow{a}_{i-1}(q_{i-2}^*)}^1 \left[\int_0^{\overleftarrow{a}_i(q_{i-1}^*)} f(a_i) da_i\right] \ldots f(a_2) da_2,
\end{aligned}
$$

and

$$
\begin{aligned}
O_i(a_1) &= P_i(q_i = 0 | q_1 = vq_1^*) \\
&= \int_0^{\overrightarrow{a}_2(q_1^*)} \int_0^{\overrightarrow{a}_3(q_1^*)} \cdots \int_0^{\overrightarrow{a}_{i-1}(q_1^*)} \left[\int_0^{\overleftarrow{a}_i(q_1^*)} f(a_i) da_i\right] \ldots f(a_2) da_2 \\
&\quad + \int_0^{\overrightarrow{a}_2(q_1^*)} \int_0^{\overrightarrow{a}_3(q_1^*)} \cdots \int_{\overrightarrow{a}_{i-1}(q_1^*)}^1 \left[\int_0^{\overleftarrow{a}_i(q_{i-1}^*)} f(a_i) da_i\right] \ldots f(a_2) da_2 \\
&\quad + \ldots \\
&\quad + \int_{\overrightarrow{a}_2(q_1^*)}^1 \int_{\overrightarrow{a}_3(q_2^*)}^1 \cdots \int_{\overrightarrow{a}_{i-1}(q_{i-2}^*)}^1 \left[\int_0^{\overleftarrow{a}_i(q_{i-1}^*)} f(a_i) da_i\right] \ldots f(a_2) da_2,
\end{aligned}
$$

where the boundaries are defined as $\overleftarrow{a}_i(q_j^*) = (q_j^*)^{d_i}$ and $\overrightarrow{a}_i(q_j^*) = \frac{1}{1-d_i}(q_j^*)^{d_i}$.
Using the Leibniz integral rule, we have:

$$
\begin{aligned}
\frac{\partial P_i(q_i = 0)}{\partial v} &= \frac{\partial \overrightarrow{a}_1(v, q_0)}{\partial v} N_i(v, q_0)^{(1)} f\left(\overrightarrow{a}_1(v, q_0)\right) + \int_0^{\overrightarrow{a}_1(v, q_0)} \frac{\partial N_i(v, q_0)^{(1)}}{\partial v} f(a_1) da_1 \\
&\quad - \frac{\partial \overrightarrow{a}_1(v, q_0)}{\partial v} O_i\left(\overrightarrow{a}_1(v, q_0)\right) f\left(\overrightarrow{a}_1(v, q_0)\right) \\
&= \int_0^{\overrightarrow{a}_1(v, q_0)} \frac{\partial N_i(v, q_0)^{(1)}}{\partial v} f(a_1) da_1 \\
&= \frac{\partial N_i(v, q_0)^{(1)}}{\partial v} F\left(\overrightarrow{a}_1(v, q_0)\right).
\end{aligned}
$$

The second equality obtains as the first and third terms cancel each other. The third equality obtains as $\{\partial N_i(v, q_0)^{(1)}\}/\{\partial v\}$ is independent of a_1. Moreover, by iteratively applying Equation (9), we obtain:

$$
\begin{aligned}
\frac{\partial P_i(q_i = 0)}{\partial v} &= \frac{\partial N_i(v, q_0)^{(1)}}{\partial v} F\left(\overrightarrow{a}_1(v, q_0)\right) \\
&= \left(\frac{\partial N_i(v, q_0)^{(2)}}{\partial v} F\left(\overrightarrow{a}_2(v, q_0)\right)\right) F\left(\overrightarrow{a}_1(v, q_0)\right) \\
&= \left(\frac{\partial N_i(v, q_0)^{(i-1)}}{\partial v} F\left(\overrightarrow{a}_{i-1}(v, q_0)\right)\right) F\left(\overrightarrow{a}_{i-2}(v, q_0)\right) \cdots F\left(\overrightarrow{a}_1(v, q_0)\right) \\
&= \frac{\partial F\left(\left(\frac{q_0}{v}\right)^{d_i}\right)}{\partial v} F\left(\overrightarrow{a}_{i-1}(v, q_0)\right) \cdots F\left(\overrightarrow{a}_1(v, q_0)\right). \\
&= (-cd_i) v^{-cd_i - 1} q_0^{cd_i} F\left(\overrightarrow{a}_{i-1}(v, q_0)\right) \cdots F\left(\overrightarrow{a}_1(v, q_0)\right)
\end{aligned}
$$

As $F\left(\overrightarrow{a}_{i-1}(v, q_0)\right) \cdots F\left(\overrightarrow{a}_1(v, q_0)\right) > 0$, we obtain $\{\partial P_i(q_i = 0)\}/\{\partial v\} < 0$. In summary, with a positive reserve, $q_0 > 0$, the probability of participation for user i strictly increases in v. ∎

We now use a two-user example, adapted from Segev and Sela (2011), to illustrate our theoretical results.

Example 1. *Consider a sequential all-pay auction with two users whose abilities are i.i.d. draws from a concave distribution function $F(x) = x^{0.5}$ with support on $[0, 1]$. In addition, the reward is $v \geq 1$.*

In this example, the equilibrium bidding function for user 1 is $q_1(a_1) = \frac{a_1^2}{4} v$. After observing 1's submission, user 2 bids according to the following equilibrium bidding function,

$$
q_2(a_2) = \begin{cases} 0 & \text{if } 0 \leq a_2 < \frac{a_1^2}{4}, \\ \frac{a_1^2}{4} v & \text{if } \frac{a_1^2}{4} \leq a_2 \leq 1. \end{cases}
$$

The likelihood that user 1 submits a positive bid is 1, while the conditional likelihood that user 2 submits a positive bid is

$$
\text{Prob}(q_2 > 0 \mid a_1) = 1 - F\left(\frac{a_1^2}{4}\right) = 1 - \frac{a_1}{2}.
$$

In addition, the likelihood that user 2 submits a positive bid is:

$$\text{Prob}(q_2 > 0) = \int_0^1 (1 - \frac{a_1}{2})\frac{1}{2\sqrt{a_1}}da_1 \approx 0.83.$$

Lastly, the expected quality for each user, Q_1, Q_2, the average and the highest quality, AQ and HQ, can be characterized as follows:

$$Q_1 = v \int_0^1 \frac{a_1^2}{4}\frac{1}{2\sqrt{a_1}}da_1 = 0.05v,$$

$$Q_2 = \int_0^1 \int_{\frac{a_1^2}{4}}^1 \frac{a_1^2}{4}vf(a_2)da_2 f(a_1)da_1 \approx 0.03v,$$

$$AQ = \frac{v}{2}\int_0^1 (2 - \frac{a}{2})\frac{a_1^2}{4}\frac{1}{2\sqrt{a_1}}da_1 \approx 0.04v,$$

$$HQ = Q_1 = 0.05v.$$

Note, with zero reserve, user i's expected quality, Q_i, is less than Q_{i-1}. Therefore, the expected highest quality is $HQ = Q_1$.

Proof of Proposition 2:
We now prove that user i's expected submission quality, $Q_i(q_i)$, strictly increases in the reward level, v.
First, when $i = 1$, we show that $\{\partial Q_1(v, q_0)\}/\{\partial v\} > 0$, i.e., $\forall\, v_2 > v_1$, $Q_1(v_2, q_0) > Q_1(v_1, q_0)$.

$$
\begin{aligned}
Q_1(v_1, q_0) &= \int_{\overleftarrow{a}_1(q_0,v_1)}^{\overrightarrow{a}_1(q_0,v_1)} q_0 f(a_1)da_1 + \int_{\overrightarrow{a}_1(q_0,v_1)}^1 v_1 q_1^* f(a_1)da_1 \\
&= \int_{(\frac{q_0}{v_1})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}} q_0 f(a_1)da_1 + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}}^1 v_1 q_1^* f(a_1)da_1 \\
&< \left[\int_{(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}} q_0 f(a_1)da_1 + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}} q_0 f(a_1)da_1\right] + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}}^1 v_1 q_1^* f(a_1)da_1 \\
&< \left[\int_{(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}} q_0 f(a_1)da_1 + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}} v_2 q_1^* f(a_1)da_1\right] + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}}^1 v_2 q_1^* f(a_1)da_1 \\
&= \int_{(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}} q_0 f(a_1)da_1 + \left[\int_{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}} v_2 q_1^* f(a_1)da_1 + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_1})^{d_1}}^1 v_2 q_1^* f(a_1)da_1\right] \\
&= \int_{(\frac{q_0}{v_2})^{d_1}}^{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}} q_0 f(a_1)da_1 + \int_{\frac{1}{1-d_1}(\frac{q_0}{v_2})^{d_1}}^1 v_2 q_1^* f(a_1)da_1 \\
&= Q_1(v_2, q_0).
\end{aligned}
$$

Next, for user $i > 1$, we define a sequence of conditional expected quality, $T_i(v, q_0)^{(j)}$, where $1 \le j < i$, as follows:

$$T_i(v, q_0)^{(1)} = Q_i(q_i | q_1 \leq q_0),$$

$$\ldots$$

$$T_i(v, q_0)^{(j)} = Q_i(q_i | q_1, \ldots, q_j \leq q_0),$$

$$\ldots$$

$$
\begin{aligned}
T_i(v, q_0)^{(i-1)} &= Q_i(q_i | q_{j<i} \leq q_0) \\
&= \int_{\overleftarrow{a}_i(q_0,v)}^{\overrightarrow{a}_i(q_0,v)} q_0 f(a_i) da_i + \int_{\overrightarrow{a}_i(q_0,v)}^{1} v q_i^* f(a_i) da_i \\
&= \int_{(\frac{q_0}{v})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v})^{d_i}} q_0 f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v})^{d_i}}^{1} v\left((1-d_i)a_i\right)^{\frac{1}{d_i}} f(a_i) da_i.
\end{aligned}
$$

Therefore, $T_i(v, q_0)^{(j)} = Q_i(q_i | q_1,,, q_j \leq q_0)$ is the conditional expected quality for user i when none of the first j bids exceeds the reserve. In particular, $T_i(v, q_0)^{(i-1)}$ is the conditional expected quality for user i when none of the previous bids exceeds the reserve, which is equivalent to user i being the first active user in the new sequence with $n - i + 1$ users.

Define another sequence of conditional expected quality for user i, $S_i(v, a_j)$, where $1 \leq j < i$, as follows:

$$S_i(v, a_1) = Q_i(q_i | q_1 = v q_1^*),$$

$$S_i(v, a_2) = Q_i(q_i | q_1 \leq q_0, q_2 = v q_2^*),$$

$$\ldots$$

$$S_i(v, a_j) = Q_i(q_i | q_1, \ldots, q_{j-1} \leq q_0, q_j = v q_j^*),$$

$$\ldots$$

$$S_i(v, a_{i-1}) = Q_i(q_i | q_1, \ldots, q_{i-2} \leq q_0, q_{i-1} = v q_{i-1}^*).$$

Therefore, $S_i(v, a_j) = Q_i(q_i | q_1 \ldots q_{j-1} \leq q_0, q_j = v q_j^*)$ is the conditional expected quality for user i when none of the bids before user j exceeds the reserve, $q_1, \ldots, q_{j-1} \leq q_0$, and user j's bid is the equilibrium bid in the third range of her equilibrium bidding function, $v q_j^*$.

Moreover, $\forall 1 < j \leq i$, we characterize the conditional expected quality for user i when none of the first $j - 1$ bids exceeds the reserve as:

$$T_i(v,q_0)^{(j-1)} = \int_0^{\overrightarrow{a}_j(v,q_0)} T_i(v,q_0)^{(j)} f(a_j) da_j + \int_{\overrightarrow{a}_j(v,q_0)}^1 S_i(v,a_j) f(a_j) da_j. \qquad (10)$$

The first term is the conditional expected quality for user i with a random variable $q_j \le q_0$, $Q_i(q_i, q_j \le q_0 | q_1, \ldots, q_{j-1} \le q_0)$. The second term is the conditional expected quality for user i with a random variable $q_j = vq_j^* \ge q_0$, $Q_i(q_i, q_j = vq_j^* | q_1, \ldots, q_{j-1} \le q_0)$. Differentiating Equation (10) with respect to v and using the Leibniz integral rule, we obtain:

$$\frac{\partial T_i(v,q_0)^{(j-1)}}{\partial v} = \frac{\partial \overrightarrow{a}_j(v,q_0)}{\partial v} T_i(v,q_0)^{(j)} f\left(\overrightarrow{a}_j(v,q_0)\right) + \int_0^{\overrightarrow{a}_j(v,q_0)} \frac{\partial T_i(v,q_0)^{(j)}}{\partial v} f(a_j) da_j$$

$$- \frac{\partial \overrightarrow{a}_j(v,q_0)}{\partial v} S_i\left(v, \overrightarrow{a}_j(v,q_0)\right) f\left(\overrightarrow{a}_j(v,q_0)\right) + \int_{\overrightarrow{a}_j(v,q_0)}^1 \frac{\partial S_i(v,a_j)}{\partial v} f(a_j) da_j.$$

By continuity of the equilibrium bidding function at $\overrightarrow{a}_j(v,q_0)$, we have $T_i(v,q_0)^{(j)} = S_i\left(v, \overrightarrow{a}_j(v,q_0)\right)$. Therefore, the first and third terms on the RHS cancel each other, which simplifies the RHS:

$$\frac{\partial T_i(v,q_0)^{(j-1)}}{\partial v} = \int_0^{\overrightarrow{a}_j(v,q_0)} \frac{\partial T_i(v,q_0)^{(j)}}{\partial v} f(a_j) da_j + \int_{\overrightarrow{a}_j(v,q_0)}^1 \frac{\partial S_i(v,a_j)}{\partial v} f(a_j) da_j$$

$$= \frac{\partial T_i(v,q_0)^{(j)}}{\partial v} F\left(\overrightarrow{a}_j(v,q_0)\right) + \int_{\overrightarrow{a}_j(v,q_0)}^1 \frac{\partial S_i(v,a_j)}{\partial v} f(a_j) da_j, \qquad (11)$$

as $\partial T_i(v,q_0)^{(j)}/\partial v$ is independent of a_j. Furthermore, $S_i(v,a_j) = Q_i(q_i | q_1 \ldots q_{j-1} \le q_0, q_j = vq_j^*)$ is equivalent to user i's conditional expected quality with $q_j = vq_j^*$ in the zero reserve case, as q_0 is no longer binding. Thus, user i's submitted quality can take on the value of (i) user j's interior solution, or (ii) user k's interior solution, where $k \in \{j+1, \cdots, i-1\}$, or (iii) user i's own interior solution, each of which linearly increases in v by Equation (5). Therefore, $S_i(v,a_j)$ linearly increases in v and $\partial S_i(v,a_j)/\partial v > 0$.

Therefore, the expected quality for user i, $Q_i(v,q_0)$, can be rewritten as:

$$Q_i(v,q_0) = \int_0^{\overrightarrow{a}_1(v,q_0)} T_i(v,q_0)^{(1)} f(a_1) da_1 + \int_{\overrightarrow{a}_1(v,q_0)}^1 S_i(v,a_1) f(a_1) da_1.$$

Expanding $T_i(v,q_0)^{(1)}$ and $S_i(v,a_1)$, we have:

$$T_i(v,q_0)^{(1)} = Q_i(q_i = 0 | q_1 \le q_0)$$

$$= \int_0^{\overrightarrow{a}_2(v,q_0)} \int_0^{\overrightarrow{a}_3(v,q_0)} \cdots \int_0^{\overrightarrow{a}_{i-1}(v,q_0)} \left[\int_{\overleftarrow{a}_i(v,q_0)}^{\overrightarrow{a}_i(v,q_0)} q_0 f(a_i) da_i + \int_{\overrightarrow{a}_i(v,q_0)}^1 vq_i^* f(a_i) da_i \right] \ldots f(a_2) da_2$$

$$+ v \int_0^{\overrightarrow{a}_2(v,q_0)} \int_0^{\overrightarrow{a}_3(v,q_0)} \cdots \int_{\overrightarrow{a}_{i-1}(v,q_0)}^1 \left[\int_{\overleftarrow{a}_i(q_{i-1}^*)}^{\overrightarrow{a}_i(q_{i-1}^*)} q_{i-1}^* f(a_i) da_i + \int_{\overrightarrow{a}_i(q_{i-1})}^1 q_i^* f(a_i) da_i \right] \ldots f(a_2) da_2$$

$$+ \ldots$$

$$+ v \int_{\overrightarrow{a}_2(v,q_0)}^1 \int_{\overrightarrow{a}_3(q_2^*)}^1 \cdots \int_{\overrightarrow{a}_{i-1}(q_{i-2}^*)}^1 \left[\int_{\overleftarrow{a}_i(q_{i-1}^*)}^{\overrightarrow{a}_i(q_{i-1}^*)} q_{i-1}^* f(a_i) da_i + \int_{\overrightarrow{a}_i(q_{i-1})}^1 q_i^* f(a_i) da_i \right] \ldots f(a_2) da_2,$$

and

$$S_i(v, a_1) = Q_i(q_i | q_1 = vq_1^*)$$

$$= v \int_0^{\overrightarrow{a}_2(q_1^*)} \int_0^{\overrightarrow{a}_3(q_1^*)} \cdots \int_0^{\overrightarrow{a}_{i-1}(q_1^*)} \left[\int_{\overleftarrow{a}_i(q_1^*)}^{\overrightarrow{a}_i(q_1^*)} q_1^* f(a_i) da_i + \int_{\overrightarrow{a}_i(q_1^*)}^1 q_i^* f(a_i) da_i \right] \cdots f(a_2) da_2$$

$$+ v \int_0^{\overrightarrow{a}_2(q_1^*)} \int_0^{\overrightarrow{a}_3(q_1^*)} \cdots \int_{\overrightarrow{a}_{i-1}(q_1^*)}^1 \left[\int_{\overleftarrow{a}_i(q_{i-1}^*)}^{\overrightarrow{a}_i(q_{i-1}^*)} q_{i-1}^* f(a_i) da_i + \int_{\overrightarrow{a}_i(q_{i-1}^*)}^1 q_i^* f(a_i) da_i \right] \cdots f(a_2) da_2$$

$$+ \ldots$$

$$+ v \int_{\overrightarrow{a}_2(q_1^*)}^1 \int_{\overrightarrow{a}_3(q_2^*)}^1 \cdots \int_{\overrightarrow{a}_{i-1}(q_{i-2}^*)}^1 \left[\int_{\overleftarrow{a}_i(q_{i-1}^*)}^{\overrightarrow{a}_i(q_{i-1}^*)} q_{i-1}^* f(a_i) da_i + \int_{\overrightarrow{a}_i(q_{i-1}^*)}^1 q_i^* f(a_i) da_i \right] \cdots f(a_2) da_2.$$

Using the Leibniz integral rule, we have:

$$\frac{\partial Q_i(v, q_0)}{\partial v} = \frac{\partial \overrightarrow{a}_1(v, q_0)}{\partial v} T_i(v, q_0)^{(1)} f(\overrightarrow{a}_1(v, q_0)) + \int_0^{\overrightarrow{a}_1(v,q_0)} \frac{\partial T_i(v, q_0)^{(1)}}{\partial v} f(a_1) da_1$$

$$- \frac{\partial \overrightarrow{a}_1(v, q_0)}{\partial v} S_i(v, \overrightarrow{a}_1(v, q_0)) f(\overrightarrow{a}_1(v, q_0)) + \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1.$$

$$= \int_0^{\overrightarrow{a}_1(v,q_0)} \frac{\partial T_i(v, q_0)^{(1)}}{\partial v} f(a_1) da_1 + \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1$$

$$= \frac{\partial T_i(v, q_0)^{(1)}}{\partial v} F(\overrightarrow{a}_1(v, q_0)) + \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1.$$

The second equality obtains as the first and third terms cancel each other. The third equality obtains as $\{\partial T_i(v, q_0)^{(1)}\}/\{\partial v\}$ is independent of a_1. Moreover, by iteratively applying Equation (11), we obtain:

$$\frac{\partial Q_i(v, q_0)}{\partial v} = \frac{\partial T_i(v, q_0)^{(1)}}{\partial v} F(\overrightarrow{a}_1(v, q_0)) + \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1$$

$$= \left[\frac{\partial T_i(v, q_0)^{(2)}}{\partial v} F(\overrightarrow{a_2}(v, q_0)) + \int_{\overrightarrow{a_2}(v,q_0)}^1 \frac{\partial S_i(v, a_2)}{\partial v} f(a_2) da_2 \right] F(\overrightarrow{a}_1(v, q_0))$$

$$+ \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1$$

$$= \frac{\partial T_i(v, q_0)^{(2)}}{\partial v} F(\overrightarrow{a_2}(v, q_0)) F(\overrightarrow{a}_1(v, q_0)) + F(\overrightarrow{a}_1(v, q_0)) \int_{\overrightarrow{a_2}(v,q_0)}^1 \frac{\partial S_i(v, a_2)}{\partial v} f(a_2) da_2$$

$$+ \int_{\overrightarrow{a}_1(v,q_0)}^1 \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1$$

$$= \frac{\partial T_i(v, q_0)^{(i-1)}}{\partial v} F(\overrightarrow{a}_{i-1}(v, q_0)) \cdots F(\overrightarrow{a}_1(v, q_0))$$

$$+ F(\overrightarrow{a}_{i-1}(v, q_0)) \cdots F(\overrightarrow{a}_1(v, q_0)) \int_{\overrightarrow{a}_{i-1}(v,q_0)}^1 \frac{\partial S_i(v, a_{i-1})}{\partial v} f(a_{i-1}) da_{i-1}$$

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$$+ \ldots$$
$$+ \int_{\overrightarrow{a}_1(v,q_0)}^{1} \frac{\partial S_i(v, a_1)}{\partial v} f(a_1) da_1.$$

As $\forall x > 0$, $F(x) > 0$ and $\{\partial S_i(v, a_j)\}/\{\partial v\} > 0$, the sign of $\{\partial Q_i(v, q_0)\}/\{\partial v\}$ depends on $\{\partial T_i(v, q_0)^{(i-1)}\}/\{\partial v\}$.

Applying the same technique used for user 1, we show below that $\{\partial T_i(v, q_0)^{(i-1)}\}/\{\partial v\} > 0$, i.e., $\forall\, v_2 > v_1$, $T_i(v_2, q_0)^{(i-1)} > T_i(v_1, q_0)^{(i-1)}$.

$$
\begin{aligned}
T_i(v_1, q_0)^{(i-1)} &= \int_{\overleftarrow{a}_i(q_0,v_1)}^{\overrightarrow{a}_i(q_0,v_1)} q_0 f(a_i) da_i + \int_{\overrightarrow{a}_i(q_0,v_1)}^{1} v_1 q_i^* f(a_i) da_i \\
&= \int_{(\frac{q_0}{v_1})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}} q_0 f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}}^{1} v_1 q_i^* f(a_i) da_i \\
&< \left[\int_{(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}} q_0 f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}} q_0 f(a_i) da_i \right] + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}}^{1} v_1 q_i^* f(a_i) da_i \\
&< \left[\int_{(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}} q_0 f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}} v_2 q_i^* f(a_i) da_i \right] + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}}^{1} v_2 q_i^* f(a_i) da_i \\
&= \int_{(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}} q_0 f(a_i) da_i + \left[\int_{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}} v_2 q_i^* f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_1})^{d_i}}^{1} v_2 q_i^* f(a_i) da_i \right] \\
&= \int_{(\frac{q_0}{v_2})^{d_i}}^{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}} q_0 f(a_i) da_i + \int_{\frac{1}{1-d_i}(\frac{q_0}{v_2})^{d_i}}^{1} v_2 q_i^* f(a_i) da_i \\
&= T_i(v_2, q_0)^{(i-1)}.
\end{aligned}
$$

In summary, the expected quality, Q_i, strictly increases in the reward level, v. In particular, when $q_0 = 0$, the expected quality for each user linearly increases in v. ∎

Now we use a two-user sequential all-pay auction example to show the comparative statics of both the reward and reserve effect.

Example 2. *Using the parameters of Example 1, we add a reserve, $0 < q_0 < v$.*

The equilibrium bidding functions thus become:

$$
q_1(a_1) = \begin{cases} 0 & \text{if } 0 \le a_1 < \sqrt{\frac{q_0}{v}}, \\ q_0 & \text{if } \sqrt{\frac{q_0}{v}} \le a_1 < 2\sqrt{\frac{q_0}{v}}, \\ \frac{a_1^2}{4} v & \text{if } 2\sqrt{\frac{q_0}{v}} \le a_1 \le 1. \end{cases}
$$

Note, when $q_0 \ge \frac{v}{4}$, the third range of $q_1(a_1)$ does not exist.

If $0 \le a_1 \le 2\sqrt{\frac{q_0}{v}}$,

$$
q_2(a_2) = \begin{cases} 0 & \text{if } 0 \le a_2 < \frac{q_0}{v}, \\ q_0 & \text{if } \frac{q_0}{v} \le a_2 \le 1. \end{cases}
$$

If $2\sqrt{\frac{q_0}{v}} \leq a_1 \leq 1$,

$$q_2(a_2) = \begin{cases} 0 & \text{if } 0 \leq a_2 < \frac{a_1^2}{4}, \\ \frac{a_1^2}{4}v & \text{if } \frac{a_1^2}{4} \leq a_2 \leq 1. \end{cases}$$

The probability that user 1 submits a positive bid becomes:

$$P_1(q_1 > 0) = 1 - F\left(\sqrt{\frac{q_0}{v}}\right) < 1.$$

When q_0 increases, $P_1(q_1 > 0)$ decreases. When v increases, $P_1(q_1 > 0)$ increases.

Next, the probability that user 2 participates, denoted as $P_2(q_2 > 0)$, becomes:

$$1 - \left[\int_0^{2\sqrt{\frac{q_0}{v}}} \int_0^{\frac{q_0}{v}} f(a_2)da_2 f(a_1)da_1 + \int_{2\sqrt{\frac{q_0}{v}}}^1 \int_0^{\frac{a_1^2}{4}} f(a_2)da_2 f(a_1)da_1\right] \approx 1 - \left(0.94 * \left(\frac{q_0}{v}\right)^{0.75} + \frac{1}{6}\right).$$

When q_0 increases, $P_2(q_2 > 0)$ decreases. When v increases, $P_2(q_2 > 0)$ increases.

Consequently, the expected quality for each user, the average and highest quality are characterized as follows:

$$Q_1 = \int_{\sqrt{\frac{q_0}{v}}}^{2\sqrt{\frac{q_0}{v}}} q_0 * 0.5a_1^{-0.5}da_1 + v\int_{2\sqrt{\frac{q_0}{v}}}^1 \frac{a_1^2}{4} * 0.5a_1^{-0.5}da_1 \approx 0.05v + 0.13\frac{q_0^{1.25}}{v^{0.25}},$$

$$Q_2 = \int_0^{2\sqrt{\frac{q_0}{v}}} \int_{\frac{q_0}{v}}^1 q_0 * 0.5a_2^{-0.5}da_2 0.5a_1^{-0.5}da_1 + v\int_{2\sqrt{\frac{q_0}{v}}}^1 \int_{\frac{a_1^2}{4}}^1 \frac{a_1^2}{4} * 0.5a_2^{-0.5}da_2 0.5a_1^{-0.5}da_1$$

$$\approx 0.03v + 1.13\frac{q_0^{1.25}}{v^{0.75}} - 1.2\frac{q_0^{1.75}}{v^{0.75}},$$

$$AQ = \frac{Q_1 + Q_2}{2} \approx \frac{1}{2}\left(0.08v + 0.13\left(\frac{q_0^{1.25}}{v^{0.25}}\right) + 1.13\frac{q_0^{1.25}}{v^{0.75}} - 1.2\frac{q_0^{1.75}}{v^{0.75}}\right),$$

$$HQ = \int_0^{\sqrt{\left(\frac{q_0}{v}\right)}} \int_{\frac{q_0}{v}}^1 q_0 f(a_2)da_2 f(a_1)da_1 + \int_{\sqrt{\left(\frac{q_0}{v}\right)}}^{2\sqrt{\left(\frac{q_0}{v}\right)}} \int_0^1 q_0 f(a_2)da_2 f(a_1)da_1$$

$$+ \int_{2\sqrt{\left(\frac{q_0}{v}\right)}}^1 \int_0^1 v\frac{a_1^2}{4} f(a_2)da_2 f(a_1)da_1$$

$$\approx 0.05v + 1.13\frac{q_0^{1.25}}{v^{0.25}} - \frac{q_0^{1.75}}{v^{0.75}}.$$

∎

Proof of Proposition 3:
   The proof is similar to that for Proposition 1, so we omit it.

∎

Recall that, for Propositions 4 through 6, we assume that $H_i(x) = \prod_{j \neq i} F(x) = F^{n-1}(x)$ is strictly concave and that $H_i(0) = 0$. In addition, we do not assume that $F(x) = x^c$.

Proof of Proposition 4 and 6:

Case 1: Zero Reserve. We first derive the equilibrium bidding function for each user, when the reserve is zero, i.e., $q_0 = 0$. We do so by solving the following maximization problem for each user i:

$$\max_{q_i}\{v \prod_{j \neq i} F_j(q_j < q_i) - \frac{q_i}{a_i}\}. \tag{12}$$

As we characterize a symmetric equilibrium, we omit i in subsequent proofs. We define the inverse of $q(a)$ as $a(q)$.

$$\max_q\{vH(a(q)) - \frac{q}{a}\}. \tag{13}$$

As $H(a(q)) = F^{n-1}(a(q))$, the first-order condition is:

$$vf(a(q))(n-1)F^{n-2}(a(q))a'(q) - \frac{1}{a} = 0.$$

As $a(q)$ is the inverse of $q(a)$, then $a'(q) = \frac{1}{q'(a)}$ and we have:

$$q'(a) = a(n-1)vF^{n-2}(a)f(a).$$

We next integrate $q'(a)$ from 0 to a:

$$q(a) = (n-1)v \int_0^a sF^{n-2}(s)f(s)ds + C.$$

As $q(0) = 0$, we have $C = 0$. Therefore, the equilibrium bidding function becomes:

$$q(a) = (n-1)v \int_0^a sF^{n-2}(s)dF(s) \tag{14}$$
$$= v\left[aF^{n-1}(a) - \int_0^a F^{n-1}(s)ds\right].$$

The second-order condition is satisfied by following the same proof in Moldovanu and Sela (2001).

By Equation (14), $q(a) \geq 0$, $\forall\, a > 0$. Additionally, $a = 0$ is a measure zero event. Therefore, with a zero-reserve, the probability of participation for any user i, $1 - P_i(q_i = 0)$, is 1 in simultaneous all-pay auctions.

Case 2: Positive Reserve. We now consider the positive reserve case, i.e., $q_0 > 0$.

When $q_0 > 0$, we solve the same maximization problem as (12) with an additional constraint, $q_i \geq q_0$.

$$\max_{q_i}\{v \prod_{j \neq i} F_j(q_j < q_i) - \frac{q_i}{a_i}\}$$

$$s.t. \qquad q_i \geq q_0. \tag{15}$$

To characterize the equilibrium bidding function, we define two boundaries as:

$$\overleftarrow{a} = \frac{\frac{q_0}{v}}{H(\frac{q_0}{v})}, \text{ and } q_0 = v[\overrightarrow{a}F^{n-1}(\overrightarrow{a}) - \int_0^{\overrightarrow{a}} F^{n-1}(s)ds].$$

These boundaries partition the support of abilities into three ranges:

1. When $0 \leq a < \overleftarrow{a}$, the expected payoff from submitting a positive bid is negative. Thus, the user should submit a zero bid.

2. When $\overleftarrow{a} \leq a < \overrightarrow{a}$, as $q_0 > v\left[aF^{n-1}(a) - \int_0^a F^{n-1}(s)ds\right]$, bidding q_0 dominates $v[aF^{n-1}(a) - \int_0^a F^{n-1}(s)ds]$. Therefore, the constraint is binding, and we obtain a corner solution.

3. When $\overrightarrow{a} \leq a \leq 1$, Equation (14) is the interior solution of the constrained optimization problem (15) while the constraint is not binding.

Summarizing the above analysis, we characterize the equilibrium bidding function for user i as follows:

$$q(a) = \begin{cases} 0 & \text{if } 0 \leq a \leq \overleftarrow{a}, \\ q_0 & \text{if } \overleftarrow{a} \leq a \leq \overrightarrow{a}, \\ v[aF^{n-1}(a) - \int_0^a F^{n-1}(s)ds] & \text{if } \overrightarrow{a} \leq a \leq 1, \end{cases} \tag{16}$$

Note that when $q_0 > v[1 - \int_0^1 F^{n-1}(s)ds]$, the third range of Equation (16) does not exist.

Now we examine the reward and the reserve effect on participation in simultaneous all-pay auctions, i.e., $P(q = 0) = F(\overleftarrow{a}) = F(\frac{q_0/v}{H(q_0/v)})$ strictly decreases in v and strictly increases in q_0.

Defining $Z(a) \equiv \frac{a}{H(a)}$, we first show $Z(a)$ strictly increases in a.

Differentiating Z(a) w.r.t. a, we obtain:

$$\frac{dZ(a)}{da} = \frac{H(a) - aH'(a)}{H^2(a)}.$$

As $H(a)$ is strictly concave and $H(0) = 0$, $\forall a > 0$, we have $H(a) > aH'(a)$. Therefore,

$$\frac{dZ(a)}{da} = \frac{H(a) - aH'(a)}{H^2(a)} > 0.$$

Consequently, $Z(a)$ strictly increases in a. Moreover, as $F(x)$ also strictly increases in x, when v increases, $F(\overleftarrow{a})$ strictly decreases. Therefore, the probability of participation, $P(q > 0)$, strictly increases with v.

Similarly, when q_0 increases, $F(\overleftarrow{a})$ strictly increases and the probability of participation, $P(q > 0)$, strictly decreases.

∎

Proof of Proposition 5:

Using Equation (16), the expected quality for each user i in simultaneous all-pay auctions is

$$Q = \int_{\overleftarrow{a}}^{\overrightarrow{a}} q_0 f(s)ds + \int_{\overrightarrow{a}}^1 v\left[aH(a) - \int_0^a H(s)ds\right] f(s)ds,$$

where $H(s) = F^{n-1}(s)$.

When the reward size, v, increases, $\overleftarrow{a}$ strictly deceases by following the proof of Proposition 4. Now we show that $\overrightarrow{a}$ also strictly decreases in v.

As $q_0 = v[\overrightarrow{a} F^{n-1}(\overrightarrow{a}) - \int_0^{\overrightarrow{a}} F^{n-1}(s)ds]$, we obtain:

$$\frac{q_0}{v} = \overrightarrow{a} F^{n-1}(\overrightarrow{a}) - \int_0^{\overrightarrow{a}} F^{n-1}(s)ds.$$

Define $M(\overrightarrow{a}) \equiv \frac{q_0}{v}$, which has a corresponding inverse function $\overrightarrow{a} \equiv M^{-1}(\frac{q_0}{v})$. We first show that $M(\overrightarrow{a})$ is strictly increases in $\overrightarrow{a}$.

Applying the Leibniz integral rule and differentiating $M(\overrightarrow{a})$ w.r.t. $\overrightarrow{a}$, we obtain:

$$\frac{dM(\overrightarrow{a})}{d\overrightarrow{a}} = (n-1)\overrightarrow{a} F^{n-2}(\overrightarrow{a})f(\overrightarrow{a}) > 0.$$

As $M(\overrightarrow{a})$ strictly increases in $\overrightarrow{a}$, the inverse function $\overrightarrow{a} \equiv M^{-1}(\frac{q_0}{v})$ also strictly increases in $t \equiv \frac{q_0}{v}$. Therefore, when v increases, t strictly decreases and $\overrightarrow{a}$ strictly decreases.

Similar to the proof for user 1's expected quality in sequential all-pay auctions (Proposition 2), the expected quality for each user in simultaneous all-pay auctions strictly increases in v. ∎

Appendix B: Sample Tasks and List of Taskcn IDs and URLs for All Tasks

We provide sample translation tasks for both the personal statements and company introductions, with excerpts of a reserve submission and a machine translation for each task. For the programming tasks, we also provide a sample task and the corresponding solutions. For each task used in our experiment, we provide the complete list of Taskcn IDs and URLs.[21] Interested readers can browse each task and the corresponding solutions from the Taskcn online archive by directly clicking on the URLs or by entering the TaskID from the search window on `http://www.taskcn.com/.`

1. **Sample Personal Statement**

   (a) **TaskID 40883** (excerpt)

   > 个人申请文书
   >
   > 带着与生俱来的好奇心，从社会现象，科学迷题，到现代技术，
   >
   > 我对很多事物都充满了好奇。也因为这样，我选择了信息管理
   >
   > 系统作为本科专业，并在数学，计算机科学以及其他社会科学
   >
   > 方面得到了严格的训练。。。。。。

   (b) **Reserve Submission**
   Born with strong curiosity about the world, I am interested in diverse topics including social phenomena, scientific puzzles, and modern technologies. Therefore, I chose Management Information Systems as my undergraduate major, in which I received rigorous training in mathematics, computer science and other social sciences.

   (c) **Machine Translation**
   With innate curiosity, from a social phenomenon, the scientific puzzle to modern technology, I have a lot of things are full of curiosity. Also for this reason that I chose the information management system as a degree, get a rigorous mathematics, computer science and other social science training.

---

[21]The URLs were effective as of September 25, 2011.

2. **Sample Company Introduction**

   (a) **TaskID 40614** (excerpt)

公司简介

tp 汽车保险股份有限公司是 2004 年 12 月经中国保险监督管理
委员会批准设立的全国性金融机构，是中国第一家专业汽车保
险公司。公司总部设在上海浦东陆家嘴金融区，注册资本 5.5
亿元人民币，主要经营机动车交通事故责任强制保险和机动车
商业保险，同时还经营企业财产险、家财险、货运险、责任险、
短期意外险和健康险等业务。。。。。。

   (b) **Reserve Submission**

TP Auto Insurance Co., Ltd. is a national financial institute approved by China Insurance Regulatory Commission on December 2004. It is the first professional Chinese Auto insurance company. The headquarters are in the Pu Dong Lu Jiazui financial district in Shanghai, with a registered capital of 550 million RMB. The company mainly operates Compulsory Traffic Accident Liability Insurance for Motor Vehicles and Commercial Insurance for Motor Vehicles. It also operates Enterprise Property Insurance, Family Property Insurance, Shipping insurance, Liability Insurance, Short-time Accident Insurance and Health Insurance, etc.

   (c) **Machine Translation**

TP Automobile Insurance Company is a 12 period in 2004 the China Insurance Regulatory Commission approved the establishment of a national financial institutions, is China's first professional automobile insurance. The company is headquartered in Shanghai Pudong Lujiazui financial district, the registered capital of 550 million yuan, mainly engaged in the compulsory motor vehicle traffic accident liability insurance and commercial insurance of motor vehicles, as well as property insurance enterprises, home Insurance, cargo insurance, liability insurance short-term accident insurance and health insurance services.

3. **Sample Programming Task**

   (a) **TaskID 40707**

Website needs a password security checking function. Show input characters as encoded dots when user types password. Generate an information bar to indicate the security level of the password, considering these factors:

    i. length of the password;
    ii. mixture of numbers and characters;

      iii. mixture of upper and lower case letters;

      iv. mixture of other symbols.

    Please provide source code and html for testing.

(b) The sample solution can be found on the first author's website:
`http://sitemaker.umich.edu/liuxiao/files/spt.pdf`.

4. **Taskcn IDs and URLs for All Translation Tasks**

(a) The High-Reward-No-Reserve Treatment

40570 `http://www.taskcn.com/w-40570.html`;
41106 `http://www.taskcn.com/w-41106.html`;
40627 `http://www.taskcn.com/w-40627.html`;
41211 `http://www.taskcn.com/w-41211.html`;
40678 `http://www.taskcn.com/w-40678.html`;
41232 `http://www.taskcn.com/w-41232.html`;
40766 `http://www.taskcn.com/w-40766.html`;
41289 `http://www.taskcn.com/w-41289.html`;
40820 `http://www.taskcn.com/w-40820.html`;
41356 `http://www.taskcn.com/w-41356.html`;
40855 `http://www.taskcn.com/w-40855.html`;
41388 `http://www.taskcn.com/w-41388.html`;
40896 `http://www.taskcn.com/w-40896.html`;
41460 `http://www.taskcn.com/w-41460.html`;
40993 `http://www.taskcn.com/w-40993.html`;
41513 `http://www.taskcn.com/w-41513.html`;
41034 `http://www.taskcn.com/w-41034.html`;
41567 `http://www.taskcn.com/w-41567.html`;
41068 `http://www.taskcn.com/w-41068.html`;
41623 `http://www.taskcn.com/w-41623.html`.

(b) The High-Reward-Reserve-Without-Credit Treatment

40614 `http://www.taskcn.com/w-40614.html`;
41115 `http://www.taskcn.com/w-41115.html`;
40650 `http://www.taskcn.com/w-40650.html`;
41156 `http://www.taskcn.com/w-41156.html`;
40694 `http://www.taskcn.com/w-40694.html`;
41243 `http://www.taskcn.com/w-41243.html`;
40761 `http://www.taskcn.com/w-40761.html`;
41282 `http://www.taskcn.com/w-41282.html`;
40812 `http://www.taskcn.com/w-40812.html`;

41353 `http://www.taskcn.com/w-41353.html`;
40883 `http://www.taskcn.com/w-40883.html`;
41393 `http://www.taskcn.com/w-41393.html`;
40940 `http://www.taskcn.com/w-40940.html`;
41427 `http://www.taskcn.com/w-41427.html`;
40991 `http://www.taskcn.com/w-40991.html`;
41491 `http://www.taskcn.com/w-41491.html`;
41015 `http://www.taskcn.com/w-41015.html`;
41548 `http://www.taskcn.com/w-41548.html`;
41055 `http://www.taskcn.com/w-41055.html`;
41596 `http://www.taskcn.com/w-41596.html`.

(c) The High-Reward-Reserve-With-Credit Treatment

40612 `http://www.taskcn.com/w-40612.html`;
41103 `http://www.taskcn.com/w-41103.html`;
40646 `http://www.taskcn.com/w-40646.html`;
41175 `http://www.taskcn.com/w-41175.html`;
40695 `http://www.taskcn.com/w-40695.html`;
41235 `http://www.taskcn.com/w-41235.html`;
40764 `http://www.taskcn.com/w-40764.html`;
41294 `http://www.taskcn.com/w-41294.html`;
40816 `http://www.taskcn.com/w-40816.html`;
41360 `http://www.taskcn.com/w-41360.html`;
40863 `http://www.taskcn.com/w-40863.html`;
41384 `http://www.taskcn.com/w-41384.html`;
40919 `http://www.taskcn.com/w-40919.html`;
41430 `http://www.taskcn.com/w-41430.html`;
40985 `http://www.taskcn.com/w-40985.html`;
41470 `http://www.taskcn.com/w-41470.html`;
41008 `http://www.taskcn.com/w-41008.html`;
41534 `http://www.taskcn.com/w-41534.html`;
41046 `http://www.taskcn.com/w-41046.html`;
41606 `http://www.taskcn.com/w-41606.html`.

(d) The Low-Reward-No-Reserve Treatment

40585 `http://www.taskcn.com/w-40585.html`;
41176 `http://www.taskcn.com/w-41176.html`;
40673 `http://www.taskcn.com/w-40673.html`;
41199 `http://www.taskcn.com/w-41199.html`;
40699 `http://www.taskcn.com/w-40699.html`;
41261 `http://www.taskcn.com/w-41261.html`;

40765 http://www.taskcn.com/w-40765.html;

41291 http://www.taskcn.com/w-41291.html;

40826 http://www.taskcn.com/w-40826.html;

41364 http://www.taskcn.com/w-41364.html;

40897 http://www.taskcn.com/w-40897.html;

41385 http://www.taskcn.com/w-41385.html;

40945 http://www.taskcn.com/w-40945.html;

41459 http://www.taskcn.com/w-41459.html;

40995 http://www.taskcn.com/w-40995.html;

41509 http://www.taskcn.com/w-41509.html;

41035 http://www.taskcn.com/w-41035.html;

41566 http://www.taskcn.com/w-41566.html;

41078 http://www.taskcn.com/w-41078.html;

41636 http://www.taskcn.com/w-41636.html.

(e) The Low-Reward-Reserve-Without-Credit Treatment

40591 http://www.taskcn.com/w-40591.html;

41123 http://www.taskcn.com/w-41123.html;

40663 http://www.taskcn.com/w-40663.html;

41190 http://www.taskcn.com/w-41190.html;

40704 http://www.taskcn.com/w-40704.html;

41234 http://www.taskcn.com/w-41234.html;

40759 http://www.taskcn.com/w-40759.html;

41284 http://www.taskcn.com/w-41284.html;

40814 http://www.taskcn.com/w-40814.html;

41336 http://www.taskcn.com/w-41336.html;

40882 http://www.taskcn.com/w-40882.html;

41410 http://www.taskcn.com/w-41410.html;

40939 http://www.taskcn.com/w-40939.html;

41439 http://www.taskcn.com/w-41439.html;

40988 http://www.taskcn.com/w-40988.html;

41492 http://www.taskcn.com/w-41492.html;

41023 http://www.taskcn.com/w-41023.html;

41533 http://www.taskcn.com/w-41533.html;

41065 http://www.taskcn.com/w-41065.html;

41610 http://www.taskcn.com/w-41610.html;

(f) The Low-Reward-Reserve-With-Credit Treatment

40625 http://www.taskcn.com/w-40625.html;

41111 http://www.taskcn.com/w-41111.html;

40643 http://www.taskcn.com/w-40643.html;

41171 http://www.taskcn.com/w-41171.html;
40691 http://www.taskcn.com/w-40691.html;
41242 http://www.taskcn.com/w-41242.html;
40754 http://www.taskcn.com/w-40754.html;
41288 http://www.taskcn.com/w-41288.html;
40822 http://www.taskcn.com/w-40822.html;
41343 http://www.taskcn.com/w-41343.html;
40793 http://www.taskcn.com/w-40793.html;
41383 http://www.taskcn.com/w-41383.html;
40941 http://www.taskcn.com/w-40941.html;
41431 http://www.taskcn.com/w-41431.html;
40981 http://www.taskcn.com/w-40981.html;
41473 http://www.taskcn.com/w-41473.html;
41029 http://www.taskcn.com/w-41029.html;
41526 http://www.taskcn.com/w-41526.html;
41056 http://www.taskcn.com/w-41056.html;
41576 http://www.taskcn.com/w-41576.html.

5. **Taskcn IDs and URLs for All Programming Tasks**

   (a) The High-Reward Treatment

   40599 `http://www.taskcn.com/w-40599.html`;
   41053 `http://www.taskcn.com/w-41053.html`;
   40652 `http://www.taskcn.com/w-40652.html`;
   41142 `http://www.taskcn.com/w-41142.html`;
   40707 `http://www.taskcn.com/w-40707.html`;
   41423 `http://www.taskcn.com/w-41423.html`;
   40778 `http://www.taskcn.com/w-40778.html`;
   41454 `http://www.taskcn.com/w-41454.html`;
   40846 `http://www.taskcn.com/w-40846.html`;
   41519 `http://www.taskcn.com/w-41519.html`;
   40904 `http://www.taskcn.com/w-40904.html`;
   41664 `http://www.taskcn.com/w-41664.html`;
   40999 `http://www.taskcn.com/w-40999.html`;
   42091 `http://www.taskcn.com/w-42091.html`.

   (b) The Low-Reward Treatment

   40654 `http://www.taskcn.com/w-40654.html`;
   41144 `http://www.taskcn.com/w-41144.html`;
   40726 `http://www.taskcn.com/w-40726.html`;
   41424 `http://www.taskcn.com/w-41424.html`;
   40780 `http://www.taskcn.com/w-40780.html`;
   41456 `http://www.taskcn.com/w-41456.html`;
   40848 `http://www.taskcn.com/w-40848.html`;
   41574 `http://www.taskcn.com/w-41574.html`;
   40959 `http://www.taskcn.com/w-40959.html`;
   41665 `http://www.taskcn.com/w-41665.html`;
   41000 `http://www.taskcn.com/w-41000.html`;
   41983 `http://www.taskcn.com/w-41983.html`;
   41054 `http://www.taskcn.com/w-41054.html`;
   42092 `http://www.taskcn.com/w-42092.html`.

Appendix C: Rating Instructions

To improve the reliability of students' ratings, we conducted training sessions before the rating sessions began. For the translation tasks, we gave raters one sample personal statement and company introduction, then asked them to rate the difficulty of both questions.[22] We also gave them two submissions for each task and asked them to rate the quality of each submission. One of the submissions was written by either the personal statement provider or our two undergraduate research assistants, while the other was randomly drawn from the submissions that we received from the pilot session. For the programming task, we followed the same procedure with two sample tasks. In addition, to help raters develop and refine their own personal rating scales, we asked them to individually give reasons for their rating scores for each task-submission pair.

C.1. Translations

All translation raters were asked to provide ratings for the following items for each task-submission pair:

1. Please rate the question for the following factors:

    (a) Please rate the effort level in terms of time needed for a proficient translator.
        (0: 0-0.5 hour; . . .; 10: 5-7 days)

    (b) It requires deep understanding of a specific field.
        (1 = strongly disagree; . . .; 7 = strongly agree)

    (c) It requires highly advanced English writing skills.
        (1 = strongly disagree; . . .; 7 = strongly agree)

    (d) Please rate the overall translation difficulty of the original text.
        (1 = very easy; . . .; 7 = very difficult)

2. Please rate the answer for the following factors: (1 = strongly disagree; . . .; 7 = strongly agree)

    (a) Overall, the translation is accurate.
    (b) The translation is complete.
    (c) The translator has a complete and sufficient understanding of the original document.
    (d) The translation is coherent and cohesive (it can be smoothly read).
    (e) The translation properly conforms to the correct usage of English expression.

3. Please rate the overall quality of this translation work.

    (1 = very low quality; . . .; 7 = very high quality.)

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[22]These two tasks were used in the pilot session before the experiment. The purpose of the pilot session was to check the reward and task duration parameters.

C.2. Programming

For the programming tasks, raters were asked to rate the following items for each task-submission pair:

1. Please rate the task for the following factors:

   (a) Please rate the task by the level of expertise it requires to fulfill the task description:

      1: The task requires minimal knowledge and expertise in programming in the language. A person with normal college education can accomplish it without training.
      2: ...
      3: ...
      4: The task requires substantial knowledge and expertise comparable to that of a trained programmer with 2-3 years of relevant programming experience in the language.
      5: ...
      6: ...
      7: The task requires very high level of knowledge and expertise that professional expert would have. The expert should have deep and comprehensive understanding on the philosophy of the language, as well as more than 5 years of professional experience.

   (b) Please rate the task on the required effort level in terms of time needed for a trained programmer to accomplish the task as described. A trained programmer is defined as someone with 2 - 3 years of programming experience with Javascript or other language as required. The work can be done within (including everything such as coding, testing, packing etc.):

      0: 0-0.5 hour;
      1: 0.5 - 1 hour;
      2: 1 - 2 hours;
      3: 2 - 3 hours;
      4: 3 - 5 hours;
      5: 5 - 8 hours;
      6: 8 - 12 hours;
      7: 12 - 24 hours;
      8: 2 - 3 days;
      9: 4 - 5 days;
      10: 5 - 7 days.

2. Please rate the solution for the following factors:

   (a) **Functionality:** Please rate the solution by the degree to which it realized the function requirement as the task description. (1-7)

      1: The solution does not realize any of the required functions.

2: ...

3: ...

4: The solution realizes most of the required functions.

5: ...

6: ...

7: The solution not only realizes all required functions, but also enhances some important functions beyond the requirement, and presents thoughtful considerations.

(b) **Programming professionalism and skill:** Please rate the solution in terms of its methods, structure, and terminology involved in design, which can be directly reflected as its readability, extendability, and testability:

1: The solution shows total novice.

2: ...

3: ...

4: The solution presents basic considerations above all three perspectives. Professional skills are employed in the major areas of the coding process.

5: ...

6: ...

7: The solution is a master piece in terms of professionalism.

(c) **Time:** Please rate the solution on the effort level in terms of how much time a trained programmer needs to accomplish the present solution. A trained programmer is defined as someone with 2-3 years of programming experience with Javascript or other language as required. The work can be done within (including everything such as coding, testing, packing etc.)

0: 0-0.5 hour;

1: 0.5 - 1 hour;

2: 1 - 2 hours;

3: 2 - 3 hours;

4: 3 - 5 hours;

5: 5 - 8 hours;

6: 8 - 12 hours;

7: 12 - 24 hours;

8: 2 - 3 days;

9: 4 - 5 days;

10: 5 - 7 days.

(d) **Overall Quality:** Please rate the overall quality of this programming work.
(1 = very low quality; . . .; 7 = very high quality)

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