# Analyzing Payment-Driven Targeted Q&A Systems

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Today's online question and answer (Q&A) services are receiving a large volume of questions. It becomes increasingly challenging to motivate domain experts to provide quick and high-quality answers. Recent systems seek to engage real-world experts by allowing them to set a price on their answers. This leads to a "targeted" Q&A model where users ask questions to a target expert by paying the corresponding price. In this article, we perform a case study on two emerging targeted Q&A systems, Fenda (China) and Whale (U.S.), to understand how monetary incentives affect user behavior. By analyzing a large dataset of 220K questions (worth 1 million USD), we find that payments indeed enable quick answers from experts, but also drive certain users to game the system for profits. In addition, this model requires users (experts) to proactively adjust their price to make profits. People who are unwilling to lower their prices are likely to hurt their income and engagement over time.

CCS Concepts: • **Human-centered computing** → *Empirical studies in HCI*;

Additional Key Words and Phrases: Online Q&A service, crowdsourcing, payments

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## 1 INTRODUCTION

The active participation of domain experts has become a key factor in the success of online question and answer (Q&A) systems. With highly engaging experts, services like Quora and StackOverflow attract hundreds of millions of visitors worldwide (Yeung 2016). However, for most Q&A systems, domain experts are answering questions *voluntarily* for free. As the question volume goes up, it becomes difficult to draw experts' attention to a particular question, let alone getting answers on-demand (Srba and Bielikova 2016b).

To motivate domain experts, one possible direction is to introduce monetary incentives (Hsieh and Counts 2009). Recently, a payment-based Q&A service called *Fenda* (Fenda 2017) is rising quickly in China. Fenda is a social network app that connects users to well-known domain experts and celebrities to ask questions with payments. Launched in May 2016, Fenda quickly gained 10 million registered users, 500K paid questions, and 2 million USD revenue in the first 2 months (Xuanmin 2016). The success of Fenda has created a new wave of payment-based Q&A services in China (Zhihu, DeDao, Weibo QA) and the U.S. (Whale, Campfire.fm, Yam).

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Table 1. Summary of Key Findings for Fenda and Whale

| Key Finding | Fenda | Whale |
|---|---|---|
| High question answering speed? | ✓ | ✓ |
| High level of engagement of users? | ✓ | ✓ |
| Potentially problematic user behavior? | ✓ | ✓ |
| Pricing strategy predicts user income? | ✓ | / |

Fenda focuses on verified, real-world domain experts, which is different from earlier payment-based Q&A services driven by an anonymous crowd (e.g., Google Answers, ChaCha (Chen et al. 2010; Hsieh et al. 2010; Lee et al. 2013)). More specifically, Fenda uses a *targeted model* where users ask questions to a target expert by paying the question fee set by the expert. This model seeks to better engage and motivate experts. In addition, Fenda is the first system that explicitly rewards people for asking good questions. After a question is answered, other users in the network need to pay a small amount ($0.14) to access to the answer. This "listening fee" will be split evenly between the question asker and the answerer (Figure 1). A good question may attract enough listeners to compensate the initial question fee.

In this article, we seek to understand the effectiveness of the targeted Q&A model and the impact of monetary incentives to the Q&A system. By performing a case study on Fenda and a U.S.-based system Whale (Whale 2016), we explore the answers to a list of key questions: How does the question price affect the answering speed? What is the potential problematic user behavior caused by the monetary incentives? Whether and how could the pricing behavior predict user income and engagement level? These questions are critical for payment-based Q&A design, and Fenda and Whale provide a unique opportunity to study them.

For our analysis, we collected a large dataset of 88,540 users and 212,082 answers from Fenda (2 months in 2016), and 1,419 users and 9,199 answers from Whale (6 months in 2016–2017), involving over 1 million dollar transactions.

Our analysis makes three key findings:

— *First*, using the new incentive model, both Fenda and Whale successfully attract a small group of high-profile experts who make significant contributions to the community. Fenda experts count for 0.5% of the user population, but have contributed a quarter of all answers and nearly half of the revenue.
— *Second*, the incentive model has a mixed impact on user behavior. Monetary incentive enables quick answers (average delay 10–23 hours) and motivates users to ask good questions. However, we find a small number of manipulative users who either aggressively ask questions to make money from listeners, or collude/collaborate to improve their perceived popularity.
— *Third*, we find that different pricing strategies of users (question answerers) can affect their own engagement level. Users who proactively adjust their price are more likely to increase income and engagement level. However, certain celebrities are unwilling to lower their price, which in turn hurts their income and social engagement.

We study two Q&A systems to better generalize our results. Table 1 shows the side-by-side comparison of the research findings for Fenda and Whale. We show that most of our results are common in Fenda and Whale except the pricing behavior of users. This is mainly because there are much fewer sustainably profitable experts in Whale, and it is hard to predict user income based on the highly sparse data points.

Table 2. Fenda/Whale vs. Other Q&A Services

| Service | Q&A Model | Fee? | Mobile? | Content |
|---|---|---|---|---|
| **Fenda** | Targeted | Y | Y | Text/Audio |
| **Whale** | Targeted | Y | Y | Text/Video |
| Jisiklog | Crowdsource | Y | Y | Text |
| ChaCha | Crowdsource | Y | Y | Text |
| Google Answer | Crowdsource | Y | N | Text |
| Mahalo Answer | Crowdsource | Y | N | Text |
| Naver Q&A | Crowdsource | N | N | Text |
| Quora | Crowdsource | N | N | Text |
| Yahoo Answer | Crowdsource | N | N | Text |
| StackOverflow | Crowdsource | N | N | Text |

To the best of our knowledge, this is the first empirical study on payment-based, targeted Q&A services. Our study provides practical guidelines for other arising payment-based Q&A services (Zhihu, DeDao, Campfire.fm, Yam) and reveals key implications for future online Q&A system design. We believe this is a first step toward understanding the economy of community-based knowledge sharing.

## 2 RELATED WORK

**Online Question Answering.** In recent years, researchers have studied online Q&A services from various aspects (Srba and Bielikova 2016a). Early studies have focused on identifying domain experts (Hanrahan et al. 2012; Pal et al. 2012) and routing user questions to the right experts (Li and King 2010; Pal et al. 2013; Wang et al. 2013a). Other works focused on assessing the quality of existing questions and answers (Adamic et al. 2008; Harper et al. 2008; Ravi et al. 2014; Shah and Pomerantz 2010; Su et al. 2007; Tausczik et al. 2017; Tian et al. 2013; Yao et al. 2014) and detecting low-quality (or even abusive) content (Kayes et al. 2015). Finally, researchers also studied Q&A activities in online social networks (Gray et al. 2013; Nichols et al. 2013). As the sizes of Q&A systems rapidly grow, it becomes challenging to engage with experts for timely and high-quality answers (Srba and Bielikova 2016b).

**Crowdsourcing vs. Targeted Q&A.** As shown in Table 2, most Q&A systems rely on crowdsourcing where any users in the community can answer the question. Fenda and Whale adopt a targeted Q&A model where users can ask questions to a target expert with payments. In this targeted Q&A model, it is the answerer (e.g., the expert) who has the upper hand to set the price for their answers. This differs Fenda and Whale from the earlier crowdsourcing Q&A services (e.g., Google Answers (Chen et al. 2010), and Mahalo (Hsieh et al. 2010)), and the broader crowdsourcing marketplace (e.g., Mechanical Turk) (Kittur et al. 2008). In those crowdsourcing marketplaces, monetary incentive could affect the work quality and/or the response time (Joglekar et al. 2013; Katmada et al. 2016; Mason and Watts 2010; Ye et al. 2017).

**User Motivations in Q&A Services.** Prior works have summarized three main user motivations to answer questions online: "intrinsic," "social," and "extrinsic" (Jin et al. 2013). Intrinsic motivation refers to the psychic reward (e.g., enjoyment) that users gain through helping others (Nam et al. 2009; Yu et al. 2007). Social factors refer to the benefits of social interactions, e.g., gaining respect and enhancing reputation. Intrinsic and social factors are critical incentives for non-payment-based Q&A services (Jin et al. 2013). Extrinsic factors refer to money and virtual rewards (e.g., badges and credit points) (Grant and Betts 2013; Nam et al. 2009).

Monetary incentive is an extrinsic factor implemented in payment-based Q&A services such as Google Answers, Mahalo, ChaCha, and Jisiklog (Chen et al. 2010; Hsieh et al. 2010; Lee et al. 2012, 2013). These systems (most are defunct) are driven by an anonymous crowd instead of a social network that engages real-world experts. Users are primarily driven by financial incentives without a strong sense of community (Hsieh and Counts 2009; Lee et al. 2013). This is concerning since research shows monetary incentive plays an important role in getting users started, but it is the social factors that contribute to the persistent participation (Raban 2008).

Researchers have studied the impact of monetary incentives but the conclusions vary. Some researchers find that monetary incentives improve the answer quality (Harper et al. 2008) and the response rate (Zhu et al. 2016). Others suggest that payments merely reduce the response delay but have no significant impact on the answer quality (Chen et al. 2010; Hsieh et al. 2010; Jeon et al. 2010). Studies also show that payment-based Q&A can reduce low-quality questions since users are more selective regarding what to ask (Hsieh and Counts 2009; Hsieh et al. 2010).

## 3 RESEARCH QUESTIONS AND METHOD

As discussed above, most existing works focus on crowdsourcing Q&A systems where question askers ask questions to a general crowd. In those systems, the question askers have limited control on who will answer the question and the expertise level of the answerers. Systems like Fenda and Whale present a rare opportunity to study *targeted* question answering where the question asker knows who to ask questions to, and use monetary incentives to motivate the target experts to answer their questions. While the targeted Q&A introduces new dynamics to the relationships between users, the monetary incentives also makes user interactions even more complex. Earlier systems such as Google Answers show that monetary incentives, if not carefully designed, can lead to a wrong path where users chase financial profits and lose engagement in the long run. In this article, we use Fenda as the primary platform to investigate how monetary incentives impact user behavior and engagement. We include Whale (a younger and smaller system) for comparison and validation purposes.

We choose Fenda and Whale for two main reasons. First, Fenda and Whale represent the first targeted Q&A model with a unique incentive model to motivate both question askers and respondents. Second, the system (Fenda, in particular) has received initial success with a significant volume of data and revenue flow. We aim to understand the reasons behind their success and potential problems moving forward, which will benefit future Q&A system design.

**Background of Fenda.** Fenda is a payment-based Q&A app in China, which connects users in a Twitter-like social network. Launched in May 2016, Fenda quickly gained 10 million registered users and over 2 million U.S. dollars' worth of questions answers in the first 2 months (Xuanmin 2016).

As shown in Figure 1, Fenda has a unique monetary incentive model to reward both question askers and answerers. A user (asker) can ask another user (answerer) a question by paying the price set by the answerer. The answerer then responds over the phone by recording a 1-minute audio message. If the answerer does not respond within 48 hours, the payment will be refunded. Any other user on Fenda can listen to the answer by paying a fixed amount of 1 Chinese Yuan ($0.14), and it will be split evenly between the asker and answerer. A good question may attract enough listeners to compensate the initial cost for the asker. Users set the price for their answers and can change the price anytime. Fenda charges 10% of the money made by a user.

There are two types of users on Fenda: verified real-world experts (e.g., doctors, entrepreneurs, movie stars) and normal users. There is an *expert list* that contains all the experts that have been verified and categorized by the Fenda administrators. Users can browse questions from the social

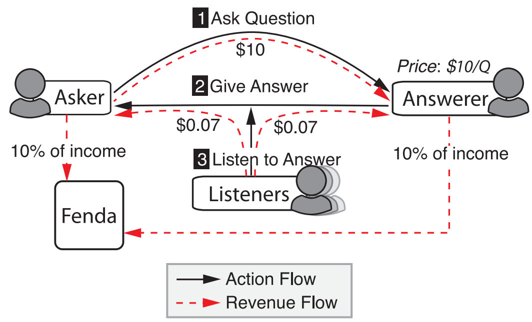



Fig. 1. Fenda's Q&A workflow and revenue flow: a user can ask another user a question by making the payment. Any other users who want to listen to the answer need to pay a small amount ($0.14) which will be split evenly between the asker and the answerer. Fenda takes 10% commission fee.

news feed or from the public stream of popular answers (a small sample). To promote user engagement, Fenda selects two to four answers daily on the public stream for free-listening for a limited time.

**Background of Whale.** Whale is a highly similar system launched in the U.S. in September 2016. By analyzing the Whale's app (as of June 2017), we noticed a few differences: First, Whale users record video (instead of audio) as their answers. Second, Whale has free questions and paid questions. For paid questions, Whale takes a higher cut (20%) from the question fee. Third, listeners use the virtual currency "whale coins" to watch the paid answers. Users can receive a few *free coins* from the platform by logging-in each day, or purchase *paid coins* in bulk ($0.29–$0.32 per coin). Only when a listener uses *paid* coins to unlock a question will the asker and answerer receive the extra payment ($0.099 each).

**Our Questions.** In the following, we introduce a list of research questions to bridge the gaps in existing literatures and explore new questions in targeted Q&A systems. More specifically, most of the existing studies focus on crowdsourcing Q&A systems and analyze how monetary incentives impact the response time and the quality of answers. It is not quite clear how monetary incentives impact user behavior and their engagement level. In addition, in targeted Q&A systems, experts become the main workforce to answer questions and drive the system moving forward. We seek to explore their roles in the targeted Q&A systems and how they price their answers in strategic ways. In the following, we use Fenda and Whale as the platform to analyze how monetary incentives impact user behavior and their engagement level. We seek to answer the following key questions.

— First, as an expert-driven Q&A system, to what extent does the system rely on experts to generate content and particularly revenue?
— Second, how does the monetary incentive affect the question answering process? Does money truly enable on-demand answers from experts? Do monetary incentives encourage users to game the system for profits?
— Third, in this targeted Q&A model, how do users set and dynamically adjust the price of their answers? How does the pricing strategy affect their income and engagement level over time?

**Data Collection.** We start by collecting a large dataset from Fenda and Whale through their mobile APIs. Our data collection focused on user profiles, which contained a full list of historical questions answered by the user. Data collections have a few challenges. First, there is no centralized list to crawl all registered users. Second, a user's follower list is not public (only the total number is

Table 3. Summary of Fenda and Whale Dataset

| Service | #Questions | #Users | #Askers | #Answerers |
|---|---|---|---|---|
| Fenda | 212,082 | 88,540 | 85,510 | 15,529 |
| Whale | 9,199 | 1,419 | 1,371 | 656 |

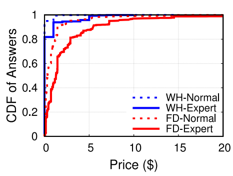



Fig. 2. Price of each answer.

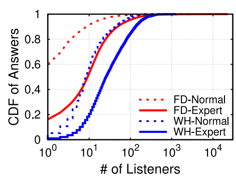



Fig. 3. # of listeners per answer.

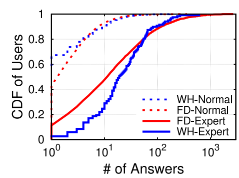



Fig. 4. # of answers per answerer.

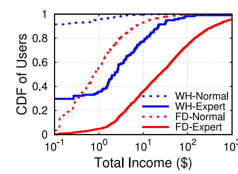



Fig. 5. Income per answerer.

visible). To these ends, we started our crawling from the expert list. For each expert, we collected their answered questions and the askers of those questions. Then we collected the askers' profiles to get their answered question list and extract new askers. We repeated this process until no new users appeared. In this way, we collected a large set of active users who asked or answered at least one question.[1]

We collected data from Fenda in July 2016. The dataset contains 88,540 user profiles and 212,082 question-answer pairs ranging from May 12 to July 27, 2016. Each question is characterized by the asker's userID, question text, a timestamp, question price, and the number of listeners. Each answer is characterized by the answerer's userID, a length of the audio, and a timestamp. UserIDs in our dataset have been fully anonymized. We briefly estimated the coverage of the Fenda dataset. Fenda announced that they had 500,000 answers as of June 27, 2016 (Xuanmin 2016). Up to the same date, our dataset covers 155,716 answers (about 31%). For Whale, we collected 1,419 user profiles and 9,199 question-answer pairs (1,114 paid questions and 8,085 free questions) from September 7, 2016 to March 8, 2017. It is difficult to estimate the coverage of the Whale dataset since there is no public statistics about Whale's user base. Table 3 shows a summary of our data.

## 4 ENGAGING WITH DOMAIN EXPERTS

We first explore the roles and impact of domain experts in the system. More specifically, we examine the contributions of domain experts to the community in terms of generating content and driving financial revenue.

Fenda maintains a list of verified experts and celebrities. As of the time of data collection, there were 4,370 verified experts classified into 44 categories by Fenda administrators. We refer to these 4,370 users as *experts* and the remaining 84,170 users as *normal users*. Whale has a similar expert list (118 experts), and we refer to the remaining 1,301 Whale users as normal users.

**Money.** Experts play an important role in driving revenue. In total, the questions in the Fenda dataset were worth $1,169,994.[2] Experts' answers generated $1,106,561, counting for a dominating 95% of total revenue in our dataset. To gauge experts' contribution in the context of the entire network, we again performed an estimation: Fenda reached 2 million revenues as of June 27 in 2016 (Xuanmin 2016). Up to this same date (June 27), expert answers in our dataset have attracted $909,876, counting for a significant 45% of the 2 million USD revenue. Figures 2 and 3 show that,

[1] Our study has received IRB approval: protocol #16-1143.
[2] We convert Chinese Yuan to USD based on $1 = 6.9 Yuan.

Table 4. Top 10 Expert Categories Based on Total Income

| Fenda | | | Whale | | |
|---|---|---|---|---|---|
| Category | Income | Experts | Category | Income | Experts |
| Health | $123K | 204 | Start-ups | $1.9K | 63 |
| Career | $81K | 222 | Tech | $1.8K | 61 |
| Business | $81K | 108 | Entertain. | $877 | 2 |
| Relation. | $73K | 90 | Snapchat | $869 | 1 |
| Movies | $52K | 84 | Motorcycle | $869 | 1 |
| Entertain. | $52K | 51 | Marketing | $471 | 20 |
| Academia | $49K | 64 | Design | $383 | 15 |
| Media | $45K | 138 | Travel | $203 | 18 |
| Real Estate | $43K | 28 | Fitness | $191 | 19 |
| Education | $39K | 174 | Finance | $141 | 8 |

on average, experts charge higher ($2.9 vs. $1.0) and draw more listeners (27 vs. 5) than normal users. Individually, experts also make more money than normal users as shown in Figure 4.

On Fenda, a small group of experts (5%) made more than $1,000. The highest earning is $33,130 by Sicong Wang, a businessman and the son of a Chinese billionaire. He answered 31 questions related to gossip and investment. He charged $500 for each of his answers, which drew 9,484 listeners ($664 extra earning) per answer on average.

On Whale, experts are also the major contributors to the revenue flow. The total collected questions on Whale are worth $2,309 and experts contributed to $2,028 (89%). Compared with Fenda (FD), Whale (WH) users earned significantly less money (Figure 5). A possible reason, as shown in Figure 2, is that most users (more than 80%) provide answers for free.

Experts of different categories have distinct earning patterns. Table 4 shows the top 10 categories ranked by the total earnings per category. In Fenda, the most popular experts are related to professional consulting. The top category is `health`, followed by `career`, `business`, and `relationship`. In the `health` category, many experts are real-world physicians and pediatricians. They give Fenda users medical advice on various (non-life-threatening) issues such as headache and flu with the expense of several dollars. Other popular categories such as `movies` contain questions to celebrities about gossip. Whale, on the other hand, has fewer experts. The highest earning experts are related to `startups` and `technology`.

In Figure 6, we further illustrate the distinct earning patterns of Fenda experts. We omit the result for Whale due to its short expert list. For each category, we compute the average price and the number of answers per expert. The red lines represent the average values across all experts, which divide them into four sections. Experts in `health`, `entertainment`, `relationship`, and `real estate` often charge high and answer many questions. These experts are among the top-earning groups; experts in `business` set the price high but do not answer many questions; less-serious categories such as `funny` and `comics` have fewer and less expensive questions. Finally, `digital` represents experts who answer lots of questions with a low price. The results also reflect the different user perceived values for different domain knowledge.

**Question Answering.** The small group of experts have contributed to a significant portion of the answers. Out of the 212K answers in the Fenda dataset, 171K (81%) are from experts. Using this dataset, we can briefly estimate the experts' contribution in the context of the entire network. On June 27 of 2016, Fenda officially announced a total of 500K answers and 10 million users (Xuanmin 2016). Up to the same date, our dataset shows the 4,370 experts (0.44% of the population) have

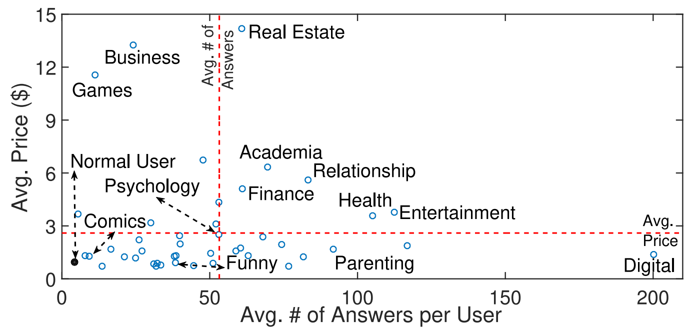



Fig. 6. Scatter plot of the average number of answers per expert and average price in each expert category (Fenda). The red lines represent the corresponding average values across all experts.

Table 5. High Level Statistics of Different Interaction Graphs

| Graph | #Nodes | # Edges | Avg. Degree | Cluster Coef. | Avg. Path Len. | Assort. Coef. | Recip. |
|---|---|---|---|---|---|---|---|
| Fenda | 87K | 154K | 3.54 | 0.02 | 4.64 | −0.16 | 0.04 |
| Whale | 1.4K | 6.4K | 9.14 | 0.20 | 2.85 | −0.20 | 0.16 |
| Quora | 159K | 833K | 10.46 | 0.05 | 3.59 | −0.03 | 0.01 |
| Facebook | 707K | 1.13M | 1.78 | 0.059 | 10.13 | 0.116 | 0.126 |
| Twitter | 4.32M | 17.0M | 3.93 | 0.048 | 5.52 | −0.025 | 0.025 |

contributed 122K answers (24.4% of total answers). As shown in Figure 5, experts have answered significantly more questions than normal users. Whale (WH) has a similar situation where 118 experts (8% of users) have contributed 4,967 answers (54% of answers).

**Asymmetric Interaction Graph.** To take a closer look into the impact of the experts on the overall user interaction patterns, we analyze the *interaction graphs*. In an interaction graph, each node represents a user, and a directed edge means a user has asked the other user a question. We compare Fenda and Whale's interaction graph with Quora (Wang et al. 2013a), Facebook (Wilson et al. 2009), and Twitter (Xu et al. 2011). Facebook's interaction graph is based on Wall post and Twitter's interaction graph is based on Retweet. Key graph statistics are shown in Table 5.

We make three key observations. First, Fenda and Whale graphs have the most negative assortativity. This metric measures how likely a user connects to other users of similar degrees. Negative assortativity means users tend to connect with others with dissimilar degrees. Fenda and Whale's assortativity value (−0.16, −0.20) shows the impact of experts: normal users tend to ask experts questions while rarely asking questions among each other. This leads to a highly asymmetrical graph structure.

Second, Fenda has a slightly lower clustering coefficient (0.02) compared to other graphs (0.048–0.059), indicating a sparser local connectivity. Intuitively, users who consult the same expert may not ask questions among each other. However, Whale has a surprisingly high clustering coefficient (0.2). This implies that users who are interested in the same expert would also ask each other questions. A closer examination shows the tight local connection is mostly driven by people from the *start-up* and *technology* categories. We suspect that this is people who already know each other in the tech community and tend to ask questions to each other.

Finally, Fenda's reciprocity value is higher than Quora and Twitter, but not as high as Facebook. A closer analysis shows that only 12% of the bidirectional edges are related to experts. Connections between experts and normal users are still highly asymmetrical. On the other hand, Whale has the

Table 6. Pearson Correlation between a User's Answer Price and Key Behavior Metrics

| Pearson Correlation | Fenda | Whale |
|---|---|---|
| # Followers vs. Answer Price | 0.53* | 0.30* |
| Avg. # Listeners vs. Answer Price | 0.65* | 0.08* |
| # Questions Answered vs. Answer Price | 0.04* | 0.14* |
| Avg. Response Time vs. Answer Price | 0.01 | −0.07 |

*indicates significant correlation with $p < 0.05$.

highest reciprocity value, meaning the connections between experts and normal users are not as imbalanced as Fenda. This again is caused by the tight bidirectional connections between people from the start-up and technology communities.

Our results suggest that dominance of domain experts on Fenda has led to asymmetric interaction patterns, differentiating Fenda from typical online social networks. Whale, on the other hand, has community-like structures. On Whale, people who interacted with the same experts are also likely to interact with each other. This is particularly true in the "*start-up*" communities.

**Engagement.** We quickly examine whether users are more engaged on Fenda and Whale, compared to non-payment-based services (e.g., StackOverflow). We use the mean value of the number of answers per day per user as a proxy for engagement ($e$). On Fenda, the value is 0.51 for experts and 0.006 for normal users. On Whale, the value is 0.23 for experts and 0.02 for normal users. As a comparison, StackOverflow's $e$ value is 0.01 (Mamykina et al. 2011). This indicates that experts are more engaged on Fenda and Whale.

After discussing the engagement level of answers, we also examine the engagement level of askers. We use the mean value of the number of questions per day per user as a proxy for engagement ($e'$). The $e'$ value of StackOverflow is 0.004, which is smaller than $e$. This is because in Stackoverflow one question can receive several answers. Overall, there are more answers than questions. On the other hand, the $e'$ value for Fenda and Whale for normal users are 0.006 and 0.02, respectively. This suggests that the normal users are more engaging than those in StackOverflow (i.e., asking more questions).

## 5 IMPACT OF MONETARY INCENTIVES

So far we show that Fenda and Whale are highly dependent on domain experts' contribution. Then the question is how to motivate experts to deliver timely and high-quality answers. In this section, we perform extensive analysis on the monetary incentive model to understand its impact on user behavior. Noticeably, Fenda and Whale use money to reward both question answerers and askers. Below, we first analyze *answerers* to understand whether payments lead to on-demand responses. Then we focus on *askers* analyzing whether and how users make money by asking the right questions. Finally, we seek to identify *abnormal users* who strategically game the system for profits.

### 5.1 Answerers

To motivate users (particularly domain experts), both Fenda and Whale allow users to determine the price for their answers. In the following, we investigate how money affects the way users answer questions. Particularly, we examine if monetary incentives truly enable on-demand quick answers.

**Setting the Answer Price.** To understand how users set a price for their answers, we calculate the Pearson correlation (Sheskin 2007) between a user's price and different behavior metrics. In Table 6,

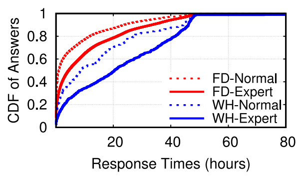



Fig. 7. Response time of answers.

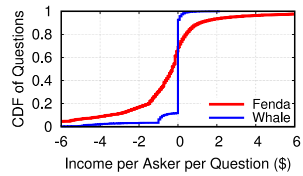



Fig. 8. Income of askers per question.

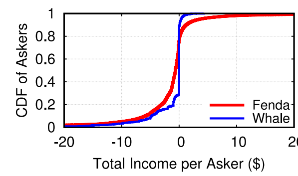



Fig. 9. Total income of askers.

Table 7. Average Response Time of the First Answer (in Hours)

| Service Name | Avg. Resp. Time (hr) | Payment Based? | Crowdsourcing or Targeted? |
|---|---|---|---|
| Yahoo Answers | 8.25 | N | Crowdsourcing |
| Fenda | 10.4 | Y | Targeted |
| Whale | 23.6 | Y | Targeted |
| Google Answers | 36.9 | Y | Crowdsourcing |
| Stack Overflow | 58.0 | N | Crowdsourcing |

We compare Fenda and Whale with different Q&A sites including Yahoo Answers (Wu and He 2014), Google Answers (Edelman 2011), and StackOverflow (Mamykina et al. 2011).

we observe that the price has positive and significant correlations with the number of followers, listeners, and answered questions. A possible explanation is that users with many followers and listeners are real-world celebrities who have the confidence to set a higher price. The higher price may also motivate them to answer more questions. Note that these are correlation results, which do not reflect causality.

Surprisingly, there is no significant correlation between price and response time (for both Fenda and Whale). This is different from existing results on crowdsourcing markets, where an asker can use a higher payment to collect answers more quickly (Hsieh et al. 2010; Katmada et al. 2016; Mason and Watts 2010).

**Answering On-Demand?** We further examine the response time to see if monetary incentives truly enable answering questions on-demand. As shown in Figure 7, answers arrive fast on Fenda: 33% of answers arrived within an hour and 85% arrived within a day. Note that there is a clear cut-off at 48 hours. This is the time when un-answered questions will be refunded, which motivates users to answer questions quickly. After 48 hours, users can still answer those questions for free. We find that only 0.7% of the answers arrived after the deadline, but we cannot estimate how many questions remain unanswered due to the lack of related data. Despite the high price charged by experts, experts respond slower than normal users.

The result for Whale is very similar. Figure 7 shows that for *paid* questions, 50%–70% of answers arrived within a day and normal users respond faster than experts. Comparing to Fenda, Whale has a slightly longer delay possibly because recording a video incurs more overhead than recording a voice message.

We then compare Fenda and Whale with other Q&A systems in Table 7. The response delay in Fenda and Whale is shorter than that of Google Answers and StackOverflow, but longer than that of Yahoo Answers. As payment-based systems, Fenda/Whale beats Google Answers probably because Fenda/Whale only asks for a short audio/video, while Google Answers require lengthy text. Compared to Yahoo Answers, we believe it is the crowdsourcing factor (i.e., a large number of potential answerers) that plays the role. Systems like Yahoo Answers crowdsource questions to a whole community where anyone could deliver the answer. Instead, Fenda/Whale's question is

Table 8. Two Sample $t$-Test Compares the Behavior Metrics for Askers with Positive Income and Those with Negative Income

| | Fenda | | | Whale | | |
|---|---|---|---|---|---|---|
| Behavior Metric | Askers \$>0 | Askers \$≤0 | $p$ | Askers \$>0 | Askers \$≤0 | $p$ |
| Avg. Followers | 2,155.5 | 3,758.5 | * | 750.2 | 790.0 | |
| Avg. Listeners | 55.2 | 16.9 | * | 28.3 | 38.1 | * |
| Avg. Price | 1.58 | 4.58 | * | 0.0 | 0.3 | * |
| Avg. Questions | 3.99 | 1.86 | * | 5.4 | 6.6 | |

*indicates the differences between the two types of askers are significant with $p < 0.05$.

targeted to a single user. The answerer is likely to answer the question within 48 hours in order to get paid, but is not motivated to answer quicker since there is no competition.

Recently, Fenda added a new crowdsourcing channel for "medical" and "legal" questions. This channel is customer-driven: users post their questions with a cash reward, and any experts can give their answers to compete for the reward. We did a quick crawling on the crowdsourcing channel and obtained 1,344 questions. We find their average response time is 4.38 hours, which is even faster than the 8.25 hours of Yahoo Answers.

### 5.2 Askers

Fenda and Whale implement the first monetary incentive model to reward users for asking good questions. More specifically, once a user's question gets answered, this user (the question asker) can earn a small amount of money from people who want to listen to the answer. This model, if executed as designed, should motivate users to contribute high-quality questions for the community.

**Can Askers Make Money?** For each question, the question asker's income is half of listeners' payments, with Fenda's commission fee and initial question fee deducted. As shown in Figure 8, out of all questions, 40% have successfully attracted enough listeners to return a positive profit to the asker. For individual askers, Figure 9 shows 40% of them have a positive total income. This demonstrates a good chance of making profits by asking good questions on Fenda. However, for Whale, the vast majority of askers did not earn money. Part of the reason is most people only ask free questions. More importantly, Whale gives away free coins every day to motivate users to log in. If a listener uses free coins (instead of paid coins), the asker will not receive any money.

**How Do Askers Make Money?** To understand why certain users make money (and others do not), we compare askers who have positive income with those with negative income in Table 8. Specifically, we examine to whom they ask questions (i.e., the number of followers and listeners of the answerer), average question price, and total questions asked. A two-sample $t$-test (Sheskin 2007) shows the significance of the differences between the two groups of askers.

On Fenda, users of positive income are more likely to send questions to people who have more listeners and charge less. The counter-intuitive result is the *number of followers*: asking people with more followers is more likely to lose money. Our explanation is the inherent correlation between a user's number of followers and her answer price—famous people would charge higher and the money from listeners cannot cover the initial cost. Askers with a higher income often asked more questions. Again, correlation does not reflect causality: it is possible that the positive income motivates users to ask more questions, or people who asked more questions get more experienced in earning money. In Table 9, we further compare people of positive income with those of negative

Table 9. Comparing Askers with Positive and Negative Income on the Types of Experts They Asked in Fenda

| Rank | Askers w/ Income > 0 | Askers w/ Income ≤ 0 |
|---|---|---|
| 1 | Non-expert (10%) | Non-expert (25%) |
| 2 | Career (10%) | Health (12%) |
| 3 | Health (8%) | Career (7%) |
| 4 | Education (7%) | Sports (4%) |
| 5 | Others (6%) | Relationship (4%) |
| 6 | Science (5%) | Education (4%) |
| 7 | Marketing (3%) | Science (4%) |
| 8 | Writers (3%) | Media (3%) |
| 9 | Fashion (3%) | Entertainment (3%) |
| 10 | Internet (3%) | Psychology (3%) |

We list the top 10 categories and % of questions in each category.

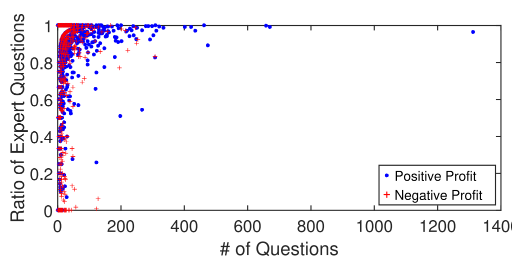



Fig. 10. Total # of questions of each asker vs. the ratio of questions to experts in Fenda. Blue dots (red crosses) represent askers with positive (negative) total income.

income regarding the "type of experts" they ask questions to. The most obvious difference is that people of negative income are more likely to ask non-expert users.

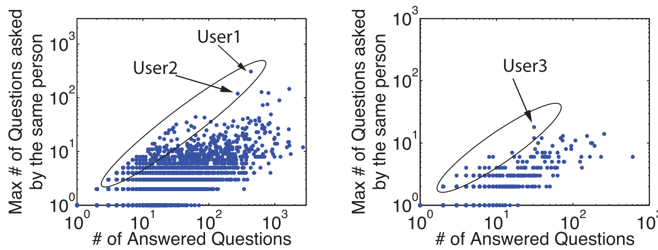
It is hard to interpret the Whale results in Table 8 since only a very small fraction of askers have a positive income (Figure 9). Noticeably, askers with positive income exclusively ask free questions (average price = 0). To this end, we also omit the expert category analysis for brevity.

### 5.3 Abnormal Users

Next, we examine suspicious users in the Q&A system who seek to game the system for financial profits.

**Bounty Hunters.** For certain users, financial gain is the primary reason to participate in payment-based Q&A systems as shown in prior works (Hsieh et al. 2010; Lee et al. 2013). On Fenda and Whale, users can make a profit not only by answering questions, but also by asking good questions. Below, we analyze askers who aggressively ask questions to gain profits (referred to as "bounty hunters").

To identify potential bounty hunters in Fenda, we examine outliers in Figure 10, which is a scatter plot for the number of questions a user asked versus the ratio of questions to experts. We find clear outliers at the right side (e.g., users with >100 questions). They asked way more questions than average, and exclusively interact with experts (ratio of expert questions is close to 1). The most extreme example is a user who asked more than 1,300 questions in 2 months, with 95% of questions to experts. This user earned \$194.20, which is much higher than the average income of askers (–\$1.95).




(a) Fenda (b) Whale

Fig. 11. Total # of questions of each answerer vs. Maximum # of questions asked by the same person. Dots in the circled area are likely the collusive users.

To further examine these outliers, we select askers who asked more than 100 questions. This gives us 111 users who count for 0.13% of askers but aggressively asked 11% of the questions. These users carefully target experts who charge a lower price ($0.80 per answer) but still draw significant listeners (15.5 per answer). The rest of the experts on average charge $2.49 and draw 23.0 listeners per answer.

We performed the same analysis on Whale and did not find such outlier users because most askers did not make a positive profit (Figure 9).

**Collusive/Collaborative Users.** In addition, there are some users who work collaboratively together to make money. For example, an asker can collude with an answerer by asking many questions (with an extremely low price) to create the illusion that the answerer is very popular. Then both the asker and the answerer can make money from the listeners of these questions. This is similar to "Sybil attacks" where multiple fake accounts are controlled by the same attacker to manipulate a social network system (Wang et al. 2013b).

To identify collaborative users, we focus on answerers whose questions are primarily asked by the same user. Figure 11 shows a scatter plot for the number of questions a user answered versus the maximum number of these questions asked by the same person. Users that are close to the diagonal are suspicious. For example, *user1* answered 435 questions and 309 (71%) were asked by the same asker. We notice that this asker did not ask any other users any questions. The questions between these two users charge $0.16 each, which is much lower than *user1*'s other questions ($0.25 on average). By using a lower price for collusion, the two users can minimize their loss—the 10% commission fee to Fenda. In this way, *user1* earned $689.9 in total and this asker also earned $244 from the listeners. The second example *user2* follows the same pattern.

Figure 11(b) shows the result of Whale. The example user (user3) answered 31 questions, 18 of which were from the same asker. This asker only asked these 18 questions and all 18 questions were free of charge. This is likely an attempt to boost user3's popularity.

**Discussion.** Our analysis shows that monetary incentives did foster questionable behavior. On the positive side, these users (bounty hunters or collaborative users) are actually working hard to come up with interesting questions in order to earn money from listeners. On the negative side, such behavior has a disruptive impact on the marketplace. For example, bounty hunters are injecting a large volume of questions to experts. The large volume of questions would act as spam to experts, blocking other users' chance to get the experts' attention. The collusive/collaborative behavior creates a fake perception of popularity, which could mislead listeners to making the wrong spending and make it unfair for honest experts.

Table 10. A List of Features for Price Change Dynamics

| id | Feature Name | Feature Description |
|---|---|---|
| 1 | Price Change Freq. | # of price change/# answers |
| 2 | Price Up Freq. | # price up/# answers |
| 3 | Price Down Freq. | # price down/# answers |
| 4 | Price Up-Down | (# price up- # price down)/# answers |
| 5 | Price Up Magnitude | Average percentage of price increase |
| 6 | Price Down Magnitude | Average percentage of price decrease |
| 7 | Consecut. Same Price | Max # consecutive same price/# answers |
| 8 | Consecut, Price Up | Max # consecutive price up/# answers |
| 9 | Consecut. Price Down | Max # consecutive price down/# answers |

## 6 DYNAMIC PRICING AND USER ENGAGEMENT

Fenda and Whale allow users to set the price for their answers. How users set this price may affect their financial income and their interaction with other users. In this section, we turn to the *dynamic* aspect to analyze how users adjust their answer prices over time and how different pricing strategies affect their engagement level. Understanding this question is critical since keeping users (particularly experts) engaged is the key to building a sustainable Q&A service.

In the following, we first identify common pricing strategies by applying unsupervised clustering on users' traces of price change. Then we analyze the identified clusters to understand what type of users they represent, and how their engagement level changes over time.

### 6.1 Identifying Distinct Pricing Strategies

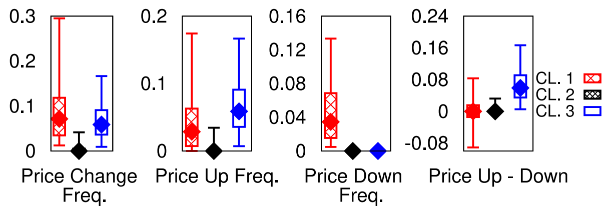
To characterize users' dynamic price change, we construct a list of features to group users with similar patterns.

**Key Features.** For each user, we model their price change as a sequence of events. Given user $i$, our dataset contains the complete list of her answers and the price for each answer. We use $P_i$ to denote user $i$'s price sequence $P_i = [p_{i,1}, p_{i,2}, \ldots, p_{i,N_i}]$ where $N_i$ is the total number of answers of user $i$. A price change event happens when $p_{i,j-1} \neq p_{i,j}$ for any $j \in [2, N_i]$. We denote the price change sequence as $C_i = [c_{i,1}, c_{i,2}, \ldots c_{i,M_i}]$ where $M_i$ is a number of times for price change and $c_{i,j}$ is a price change event (price-up, price-down, or same-price).

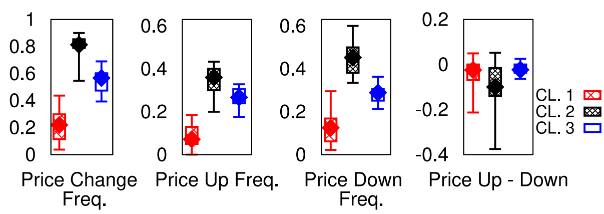
Table 10 list our nine features: the overall frequency of price change (i.e., $\frac{M_i}{N_i}$), a frequency for price-up and price-down, and the frequency difference between price-up and price-down. In addition, we consider the average price change magnitude for price-up and price-down events. Finally, we consider the maximum number of consecutive events of same-price, price-up, and price-down in the sequence.

**User Clustering.** Based on these features, we then cluster similar users into groups. First, we compute the pairwise Euclidean distance between users based on their feature vectors. This produces a fully connected similarity graph (Wang et al. 2016a) where each node is a user and edges are weighted by distance. Then, we apply a hierarchical clustering algorithm (Fortunato 2010) to detect groups of users with similar price change patterns. We choose hierarchical clustering for two reasons: (1) It does not pre-define the number of clusters. (2) It is deterministic and the clustering result does not depend on the initial seeding.

To determine the number of clusters, we use *modularity*, a well-known metric to measure clustering quality (Fortunato 2010). High modularity means users are more densely connected within




(a) Fenda




(b) Whale

Fig. 12. The distribution of the top four features for the three clusters in Fenda and Whale. We depict each distribution with box plot quantiles (5%, 25%, 50%, 75%, 95%).

each cluster than to the rest of the users. We choose the number of clusters that yields the highest modularity.

**Data.** For this analysis, we only consider users who have answered enough questions. Otherwise, discussing their dynamic price change would be less meaningful. We heuristically set the threshold as 10 (we have tested five questions and the conclusion is consistent). On Fenda, this filtering produces 2,094 users who have answered 171,322 questions (85% of all questions). On Whale, however, only 68 users meet the criteria. We still include the results of Whale for completeness.

## 6.2 Clustering Results

**Fenda.** Our method produces three clusters for Fenda (modularity 0.59). To understand the pricing strategy of each cluster, we plot their feature value distributions in Figure 12. Due to space limitation, we plot four (out of nine) most distinguishing features that have the largest variance among the three clusters selected by Chi-Squared statistic (Sheskin 2007).

- **Cluster-1 (33%):** *Frequent price up and down.* 687 users (76% are experts) who have a high price change frequency. Price up and down are almost equally frequent.
- **Cluster-2 (43%):** *Rarely changing price.* 908 users (76% are experts) who rarely change their price.
- **Cluster-3 (24%):** *Frequent price up.* 499 users (74% are experts) who increase price frequently but rarely lower their price.

We find that the three types of pricing patterns on Fenda correspond to users of different popularity. As shown in Table 11, cluster 1 represents the least popular answerers, who have the least followers and listeners but answered more questions. These users constantly adjust their price (primarily dropping the price), possibly to test the market. Cluster 3 represents the most popular experts and celebrities. They charge higher than others and keep increasing the price. Cluster 2 stands between cluster 1 and 3 in terms of popularity, and its users rarely change the price. The results indicate that popular users on Fenda have the luxury to keep increasing the price while less popular users need to carefully adjust the price to survive in the market.

Table 11. User Statistics of the Identified Clusters for Fenda and Whale

| Metrics | Fenda | | | Whale | | |
|---|---|---|---|---|---|---|
| | CL.1 | CL.2 | CL.3 | CL.1 | CL.2 | CL.3 |
| Avg. # Followers | 627.6 | 749.5 | 951.4 | 137.9 | 435.5 | 863.1 |
| Avg. # Listeners | 16.6 | 27.0 | 25.9 | 13.1 | 33.6 | 53.1 |
| Avg. Price ($) | 1.7 | 2.4 | 2.6 | 1.3 | 0.2 | 0.7 |
| Avg. # Questions | 106.5 | 68.8 | 71.4 | 2.7 | 31.0 | 38.5 |

**Whale.** Whale's three clusters only contain 68 users in total. We include the results for completeness:

— **CL.1 (60%):** *Rarely changing price.* 41 users (32% are experts) with the least frequent price change.
— **CL.2 (22%):** *Frequent price up and down.* 15 users (87% are experts) who frequently change/drop the price.
— **CL.3 (18%):** *Occasional price up and down.* 12 users (92% are experts) who occasionally change the price.

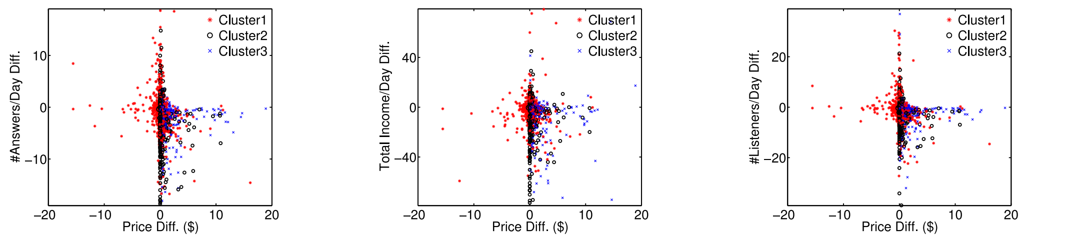
As shown in Table 11, Whale's cluster 3 contains the most popular users, followed by clusters 1 and 2. Figure 12(b) "Price Up-Down" shows the most popular users of cluster 3 are relatively balanced in terms of increasing versus decreasing the price. The less popular users of clusters 1 and 2 are more leaning toward decreasing the price. Compared to Fenda, all the clusters of Whale adjust their price rather frequently. This shows that popular users on Fenda already have the luxury to keep increasing the price. On Whale, even the most popular users are frequently adjusting their price, possibly due to the limited earning opportunities (a much lower payment per question). This is possibly due to the limited earning opportunities on Whale; unpopular users (cluster 1) tend to be the least active in adjusting the price. Meanwhile, popular users in cluster 2 and cluster 3 have to frequently adjust their price (particularly lowering the price). A closer look shows that Whale experts and celebrities are largely limited to "technology" and "start-ups" which might explain their struggles in drawing revenue from a broad audience.

### 6.3 Impact on User Engagement

Next, we analyze how price adjustments affect a user's engagement level over time. Price is a key parameter within users' control, and adjusting price is a way to test their answers' value in the market. For this analysis, we primarily focus on Fenda. The results of Whale are omitted due to the small data size.

Figure 13(a) shows the interplay between price change and engagement level over time for three identified clusters on Fenda. We quantify engagement level using a number of answers per day. To measure changes over time, we divide a user's lifespan (time between her first and last answer in our dataset) into two even parts. Then we compute the differences for average price and engagement level between the later half and first half. In a similar way, we also measure the changes in income (Figure 13(b)) and listeners (Figure 13(c)), which represent the strength of monetary and social incentives.

We observe different patterns: for clusters 2 and 3, more users are located in the lower right corner than the upper right, indicating a decrease of engagement, income, and number of listeners. A possible explanation is that there is a mismatch between the answer's price and its value, but users did not make the right adjustments. In contrast, we find a significant number of users in




(a) Engagement. (b) Income. (c) Listeners.

Fig. 13. Impact of pricing strategy on user engagement, income, and listeners in Fenda. We divide a user's lifespan into two even parts, and compute the difference between the later half and the first half. A positive value indicates an upward trend.

cluster 1 located in the upper left corner. By lowering their price, these users get to answer more questions, and receive more money and listeners over time.

Our result suggests that users need to set their price carefully to match their market value. This requires proactive price adjustments and lowering their price when necessary. Right now, highly popular users on Fenda (e.g., cluster 3) are less motivated or unwilling to lower their price, which in turn hurts their income and engagement level over time.

Note that the above analysis is a post-hoc analysis. The patterns are correlational but not necessarily causal. In addition, there is no suitable statistical analysis for the patterns we observe, which is a limitation.

## 7 IMPLICATIONS

Next, we discuss the key implications of our results to future Q&A system design.

**New Designs Introduced by Fenda and Whale.** Fenda and Whale present a first attempt to build a targeted Q&A system to engage domain experts. This type of system is suitable to users who already know which experts to ask questions to. However, this model is potentially limited to generic questions that can be answered by a large number of users. This limitation can be reflected in the *question response delay.* As shown in our previous results, with monetary incentives, Fenda and Whale achieve faster responses than most Q&A services, but are still not as fast as the crowdsourcing services such as Yahoo Answers. This is a possible reason why Fenda introduced the new crowdsourcing channel for "medica" and"legal" questions where any domain experts can answer the questions raised by the user (and the user selects the best answer to make a payment). Our result confirms that the crowdsourcing channel has a quicker response time than existing targeted Q&A channels of Fenda and Whale and Yahoo answers as well (see Section 5.1). This hybrid model helps to meet the need of different users including those who already know who to ask questions to and those who only want to get quick answers regardless of who is the answerer.

In addition, Fenda and Whale are also the first systems that try to reward users for asking good questions. Here, "good" questions refer to questions whose answers attract the interest of many other people. This leads to a mixed effect. On the positive side, users seem motivated to ask such questions to attract broad interests, which helps to bring in financial benefits to themselves. Our analysis result shows that 40% of the questions on Fenda received enough listeners to cover the asker's original cost. Our engagement analysis (Section 4) also confirms that users on Fenda and Whale are more active than systems like StackOverflow by asking more questions per day. On the negative side, this model motivates a small number of users to game the system for profits. For example, we observe "bounty hunters" who aggressively ask questions to low-priced experts, and collaborative/collusive users who work together to manipulate their perceived popularity. These behaviors are not necessarily malicious, since they did not violate the existing rules of the system. However, when more users start to engage in such behavior, the system could face the risks of driving away other users. For example, when a bounty hunter aggressively sends questions to a target expert, the large volume of questions may act as spam to block other users' chance to get their questions answered by this expert.

Although Fenda and Whale share a high level similarity, Fenda's has been more successful so far with a significantly larger user population and more user generated content. Other than cultural differences (China vs. U.S.), one possible factor is Fenda has been taking advantage of China's largest social network WeChat with over 1 billion users (Brennan 2018). First, users can directly sign up in Fenda using their WeChat accounts, which helps users to directly locate their friends and celebrity accounts. Second, Fenda's payment is made by "WeChat pay," a mobile payment service that is widely integrated with WeChat account (900 million users) (Jacobs 2018). The social network effect may have helped Fenda to quickly gain a wide adoption. A similar effect has been observed in Periscope, which has successfully bootstrapped through Twitter (Wang et al. 2016b).

**Potential Challenges Moving Forward.** While our analysis reveals insights into how users behave in targeted Q&A systems, the results also indicate future challenges that the system needs to address in the future. The *first* challenge is scalability. Unlike traditional Q&A sites, targeted Q&A heavily depends on the small number of domain experts to provide answers. If the user population continues to grow, the number of questions generated by the system will be increasingly significant. The current targeted Q&A model is hardly scalable. The *second* challenge is the content length. While the 1-minute-answer setting is helpful to gather quick answers from domain experts, it also limits the ability of the system to facilitate more in-depth discussion between questions askers and answerers. For complex questions, 1 minute is hardly enough for the domain experts to address more complex questions.

Recently, we observe that people start to address these challenges to push the targeted Q&A system to the next level. The most successful attempt so far is Zhihu Live (Live 2018). Zhihu Live provides a platform for domain experts to open up live video streaming sessions to interact with a large number of audiences while receiving payments from all the session participants. Through presentations or live Q&A sessions, one expert can engage with hundreds or even tens of thousands of people at the same time, which significantly improves the scalability of the system. According to Zhihu, the domain experts receive 11,000RMB (200USD) for a per hourly session on average. These length streaming sessions also allow in-depth discussions on complex questions from domain experts. Future research is needed to understand how users behave in Zhihu Live, and whether the incentive model is sustainable.

## 8 FUTURE RESEARCH DIRECTIONS

Our article is only a first step to understanding the design choices of the next generation of community-based Q&A systems. There are many interesting questions to be studied further in future work. First, in this work, we show that Fenda and Whale both integrate the traditional social motivators (social networks) and extrinsic incentives (payment systems) to promote Q&A activities. One future direction is to explore which incentives are more effective on different types of users (e.g., domain experts, normal users), and explore new ways to motivate users in the community. Second, targeted Q&A systems start to emerge in different countries and cultures. Future work may explore the impact of cultural differences between the users to the overall system construction and operation. This exploration is not necessarily limited to Fenda and Whale since more targeted/payment-based Q&A systems are launched in China (Zhihu Live, Weibo Q&A) and the

U.S. (Campfire, Quora Knowledge Prizes). Third, both Fenda and Whale are mobile-only Q&A services (the web interfaces are read-only). The mobile-only design allows users to record video/audio answers instead of writing down text-based answers. In the context of education and communication, audio and video are also more effective than text to enhance the social bounding between communicators (Lunt and Curran 2010; Sherman et al. 2013), which seem to be the natural choices for mobile Q&A systems. From users' perspectives, however, audio- or video-based answers are harder to quickly scan through. Future research can examine the proper communication channels (text, audio, video) for different Q&A contexts.

## 9 LIMITATIONS

Our study has a few limitations. First, our study only focuses on two services: Fenda and Whale. A broader comparison with other payment-based Q&A services can help to further generalize our results. Second, our dataset is not perfect. The crawler produces a dataset with a complete list of experts but an incomplete list of normal users. We argue that most of the missing users are likely lurkers (or inactive users) who are less influential in the community. We also used Fenda's official numbers to justify parts of our results. Third, much of our analysis is based on correlation analysis, which is a simple and powerful tool to examine the interplay of different factors in a given system. However, correlation analysis has limitations to capture more complex system dynamics (e.g., revealing causality). Future work will consider using tools such as time series analysis to study the causal relationship.

## 10 CONCLUSION

In this article, we studied targeted, payment-based Q&A systems using two empirical datasets from Fenda and Whale. The following findings were derived from our analysis structured along different aspects of users behaviors. First, unlike traditional crowdsourcing Q&A systems, we find that in targeted Q&A systems, question answering responsibility is heavily skewed to the small group of domain experts. They contributed over 90% of total revenue and contents. Second, financial incentives could indeed lead to a shorter response time than most of the traditional Q&A sites, which demonstrates that users are motivated. Third, we found that certain users tend to game the rewarding system to improve their profits or perceived popularity. These behaviors are not necessarily malicious but can impact the system fairness in the long run. This leaves room for further improvement of the Q&A system designs. Finally, we found different pricing strategies of users could affect their engagement level and income. In particular, users who are willing to lower their price can improve their income and engagements. Overall, our analysis shows the benefits of applying monetary incentives to Q&A systems (fast response, high-quality questions) as well as potential concerns (bounty hunters and over time engagement). As more similar Q&A systems are arising (Campfire.fm, DeDao, Zhihu Live), our research results can help system designers to make more informed design choices.

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