01 Jan 2022

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Recommended Citation

Ye, J. H., & Chua, C. E. (2022). Monetization for Content Generation and User Engagement on Social Media Platforms: Evidence from Paid Q&a. *IEEE Transactions on Engineering Management* Institute of Electrical and Electronics Engineers.
The definitive version is available at https://doi.org/10.1109/TEM.2022.3209534

Monetization for Content Generation and User Engagement on Social Media Platforms: Evidence from Paid Q&A

Jonathan Hua Ye and Cecil Eng Huang Chua

***Abstract*—Social media platforms want to increase their valuation in terms of total content quantity and user engagement. Monetization is often used to induce user content generation. However, research documents that while monetization increases the quantity of specific kinds of content, it does not necessarily increase the total content quantity or user engagement (i.e., platform value). Furthermore, the impact of monetization may depend on the social status of content creators. This article investigates paid question and answer (paid Q&A). Based on expectancy theory and relevant research, this article hypothesizes the effects of introducing paid Q&A on both total content quantity and user engagement and on answerers of differing statuses. We test the model using data from a natural quasi-experiment of the introduction of paid Q&A to Weibo. The key insight of our study is that total platform value in terms of both total content quantity and user engagement rises with the presence of paid Q&A. Furthermore, we find that an answerer's status negatively moderates the impact of introducing the paid Q&A feature on total content quantity but positively moderates its impact on user engagement. Our research provides insights into the causality of introducing the paid Q&A feature on platform value as well as the boundary condition of this relationship. Practically, paid Q&A is shown to be profitable to social media platforms and to increase the benefits to platform users.**

***Index Terms*—Engagement, monetization, paid Q&A, platform valuation, status seeking, total content quantity.**

I. Introduction

SOCIAL media platforms compete by offering value to their installed base of users [1]. Platform value is the benefits that users derive from using the platform and consuming its complementary goods and services [2]. The literature has conceptualized platform value as comprising two dimensions [3], [4]. The first dimension is *total content quantity,* which is the overall volume of content generated, such as the number of posts produced [5]. Greater total content quantity extends the usage scope, variety, and utility of the social media platform to users [6] and attracts users with a wide range of interests [7], [8], hence generating higher platform value. The second is *user engagement,* which is the meaningfulness and desirability of the content [1], relating to the quality dimension [4]. It can be measured using metrics such as the number of forwards and likes received [9], [10], [11]. Engaging content retains users by creating a lock-in effect for them, i.e., users will not go to other platforms for content or information [12]. Greater engagement increases the number of platform visits and time spent on the platform, leading to higher platform value [13].

Platform owners and scholars have been exploring strategic choices to maximize the value of the platform as a whole [14], [15]. One strategy often applied to increase platform value is to monetize content generation (e.g., [16], [17], [18]). In practice, monetization models include offering monetary incentives (e.g., peer awards or one-OFF cash) [19], [20] or implementing a fee-based feature (e.g., subscription, paywall, revenue sharing program, or paid question and answer) [18], [21], [22]. However, this strategy does not always work for improving the value of the *whole* platform and can have the opposite effect from that intended [23] (see Table IV in the Appendix for a summary). Notably, paying users to generate one kind of content may have a substitution effect where rather than increasing total content, paid users simply shift to producing the monetized content and reduce production of nonmonetized content [24]. Thus, despite its prevalence in practice, the literature completely overlooks how monetization affects total content quantity. Similarly, monetization may cause users to increase the volume of paid content at the expense of quality [16], [19], i.e., creating less engaging or trash content. Thus, it is unclear how monetization affects overall user engagement. Thus, how monetization impacts platform value depends on the specific mechanism used.

A new monetization model recently introduced into social media platforms is paid question and answer (Paid Q&A) [25], a fee-based feature. In paid Q&A, answerers answer questions from questioners for a fee. Other users (viewers) pay a nominal fee to view the answer within a moratorium period (i.e., three months). Questioners and answerers then share revenue from

Manuscript received 6 June 2022; revised 14 August 2022; accepted 20 September 2022. Review of this manuscript was arranged by Department Editor D. Cetindamar. *(Corresponding author: Jonathan Hua Ye.)*

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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TEM.2022.3209534.

Digital Object Identifier 10.1109/TEM.2022.3209534

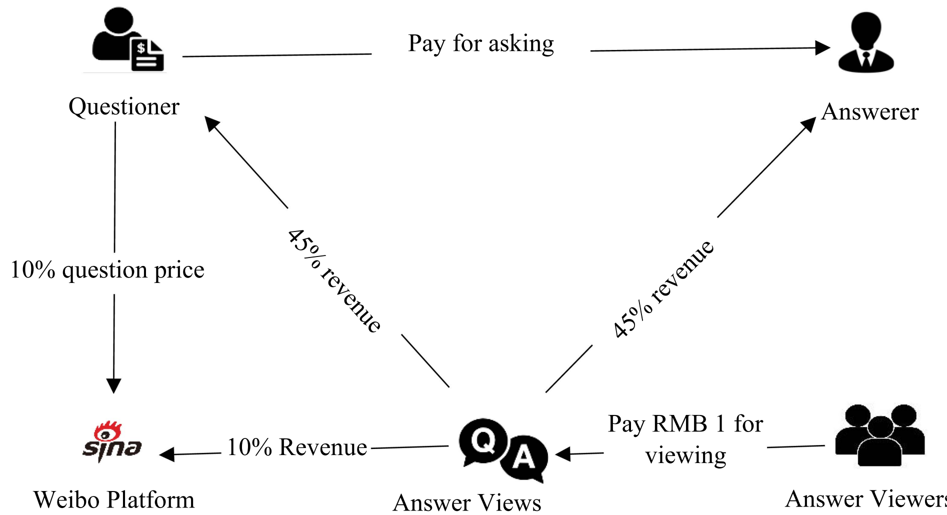

Fig. 1. Business model of Weibo Paid Q&A.

answer views [18] (see Fig. 1).[1] Once the answerer answers the proposed question, a link, which discloses the question but not the answer, is generated and automatically broadcasted to the answerer's social network, [27]. Users who want to view the answer (viewers) must pay a flat fee of one renminbi (RMB). The platform collects a fixed percentage (10%) of all viewership revenues. The remaining proceeds (90%) are shared equally between the questioner and answerer, i.e., 0.45 RMB each. We provide screenshots of the Q&A feature and a translation in Figs. 2 and 3 in the Appendix, respectively.

The paid Q&A feature has become popular on multiple social media platforms, including Quora, Zhihu, Weibo, JustAnswer, KGB, and FixYa. The overall market value of paid Q&A is huge and Quora alone has a market value of US$2 billion [28]. Given its popularity, paid Q&A is worthy of research as a new fee-based model with unique characteristics [18]. First, that particular content is monetized may incentivize answerers to contribute more and engaging content [22]. Second, paid Q&A provides a unique way for viewers to engage with high status answerers (e.g., celebrities)—receiving answers direct from these individuals [25]. The improved *interactivity* between answerers and questioners enhances viewer engagement [29], promoting their prosocial activities on the platform [30]. Viewer engagement may also be enhanced because paid Q&A creates perceived control in viewers [31]. Viewers can pay a small fee (RMB ¥1) to skip the enforced waiting period and view the answer in a real-time fashion, in effect choosing whether to delay gratification [25]. In addition, past research suggests that the Q&A model satisfies viewers' *curiosity [32]*, thus improving their engagement with others on the platform [30], [33].

Our primary research question is RQ1: How does the introduction of the paid Q&A feature affect platform value, i.e., total content quantity and user engagement? To answer this question, we draw on expectancy theory and user engagement research to develop arguments suggesting the introduction of a paid Q&A feature improves both total content quantity and user engagement.

However, monetization may not impact all platform users equally—there may be boundary conditions. For example, monetization could motivate some users to generate content but crowd out intrinsic motivations of other users for content generation [34]. Research shows that in the presence of monetary incentives, new contributors to Reddit generate more novel content than existing ones [19] whereas answerers of low reputation tend to contribute more content on Zhihu [35]. Monetary incentives seem especially important for content contributors with low status. But little research has theorized and empirically validated the moderating effects of status. Thus, we pose a related research question: *RQ2: How does an answerer's status interact with the introduction of the paid Q&A feature to affect platform value, i.e., total content quantity and user engagement?* To address the second research question, we draw on status seeking research [36], [37] to hypothesize distinct moderating effects of an answerer's status.

Our study examined these research questions using a natural quasi-experiment created when a large social media platform (Weibo) rolled out its new paid Q&A feature. We used coarsened exact matching (CEM) and a difference-in-differences (DID) approach to analyze panel data over a 12-month window centered on the month paid Q&A was introduced. We identified a sample of 202 answerers (users) who used the paid Q&A feature and paired them with 202 users who never signed up for this feature during the window of our study. We then gathered 4848 observations from these users to test the model. We find the introduction of paid Q&A causes a decline in the volume of free content, but this reduction is offset by an increase in the volume of paid Q&A content (i.e., the quantity dimension). Thus, the presence of paid Q&A overall increases total content quantity. In addition, the presence of paid Q&A increases user

[1] Any user of the platform can be a questioner, but only authorized users (e.g., online celebrities, specialists, or opinion leaders) can become answerers. This qualification vetting helps avoid the flooding of inferior content on the platform [4] [26].

engagement. Those who adopt paid Q&A witness a marked increase in their received likes and forwards from before paid Q&A, compared with the control group. We also find that the impact of introducing the paid Q&A feature on total content quantity is more pronounced for answerers of low status whereas its impact on user engagement is more pronounced for answerers of high status.

II. Related Research

A. Monetization

Research generally defines platform value as comprising two dimensions: total content quantity and user engagement [3], [4]. Substantial research (see Table IV in the Appendix) explores monetization as a mechanism for improving platform value in terms of total content quantity and user engagement. Examples include research exploring monetizing writing product reviews or financial stock reviews [16], [38], paying people to answer questions about products they own from prospective buyers [39], and monetizing content subscription [e.g., 5, 29]. Such research has generally explored how monetization affects: 1) content quantity, 2) user engagement, and 3) subpopulations on social media platforms.

Total Content Quantity. There is a general consensus that payment will induce more content production [e.g., 20, 40]. However, monetary incentives have spillover effects on social media platforms. Notably, monetizing a particular kind of content causes substitution away from producing unpaid content [e.g., 24] as people devote their limited time to producing paid content. This can sometimes backfire on such platforms, which rely on total content quantity for valuation [13] rather than the volume of specific kinds of content. For example, Qiao et al. [24] found that offering monetary incentives to review writing in Amazon will cause a decrease in subsequent contribution of free content. Thus, how monetization affects total content quantity remains unclear.

User Engagement. The literature has found the relationship between monetization and user engagement (or content quality) to be mixed. Some literature finds monetization cannot improve user engagement [e.g., 20, 41] while other literature finds user engagement decreases as a result of monetization [e.g., 24, 40]. Potentially, this is because monetization crowds out intrinsic motivation or changes cognitive processes [34], [42]. Substantial literature identifies the crowding-out effects of monetization [42], [43], where providing an extrinsic reward stifles intrinsic motivation leading to potentially lower quality. Ariely et al. [43], [44] demonstrated how payment causes behavioral focus to narrow, thereby crowding out creativity and performance.

Monetization on Subpopulations Based on Status. Status refers to the reputation, respect, prestige, and admiration afforded by others and is a fundamental human motive [45]. Past literature has demonstrated status impacts a number of critical outcomes such as knowledge contribution in online communities [46], mobile app creation on mobile phone platforms [47], impulse purchase in social commerce [48], and the sales of knowledge products [49]. Within the context of social media content creation, prior research has noted the direct impact of status on user content generation [36], [50], [51].

Beyond status' direct impact, a number of articles note post-hoc that status has an interactive effect with monetization on social media outcomes. Burtch et al. [19] noted that newcomers tend to be more active in their participation than established contributors. Wang et al. [35] postulated that low-reputation hosts tend to exhibit reputation-building behaviors in the presence of a fee-based feature. The implication of these incidental findings is that monetization may more strongly influence answerers with low or moderate status suggesting a moderating effect. However, the literature has not actively investigated this relationship.

Thus, research suggests the relationship between monetization and platform value is unclear and is driven by the specific monetization mechanism implemented. Other elements of social media platforms interact with the monetization model to shape behaviors in unexpected ways [52]. Specifically, content creator status can potentially interact with monetization to impact both total content quantity and user engagement.

B. Paid Q&A

Extant work on paid Q&A has principally focused on three areas. The first area focuses on askers, not answerers, specifically the antecedents of askers' payment intention [25], the drivers of askers' switching from free to paid Q&A [53], the impact of askers' question framing on their Q&A profit [54], and their gaming behaviors in paid Q&A [55]. For example, Zhao et al. [25] examined the antecedents of askers' payment intention from the perspective of cost and benefit. They found various drivers of the perceived value of Q&A, which in turn affects askers' payment intention. Jan et al. [55] found that certain askers game the paid Q&A system on Fenda.com for profits. They found that users can profit not only by answering questions but also by asking good questions. Askers may collude with the answerer to bait viewers to pay, e.g., asking many questions (with an extremely low question price).

The second area focuses on answerers' behaviors, e.g., the number of questions answered [27] and their response speed of answering a paid question [55]. For example, Zhao et al. [27] found that answerers' reputation and the asked price affect the number of questions they answered. Jan et al. [55] found that payments can solicit a quick response from experts. The third stream of research studies answer quality [56] and revenue [18]. Ye et al. [18] explored the drivers of answer revenue in paid Q&A. Wang et al. [35] found that introducing Zhihu paid live talk would not increase quality of answers. This stream of research is emerging and growing.

In other words, research on paid Q&A has mainly focused on exploring what incentivizes answerers to participate and produce quality answers rather than asking if the monetization mechanism itself creates benefits in the form of overall better platform value. The literature implies paid Q&A improves overall platform value [18], [27] but does not theorize about nor empirically test the relationship. Furthermore, the literature assumes homogeneous answerers [29], [57]. As we highlight previously, there is potentially an interaction effect between the introduction of paid Q&A and status on answerer behavior.

Thus, while the literature has much to say on the relationship between monetization and platform value, it does not clearly

TABLE I
GAP IDENTIFICATION AND POTENTIAL CONTRIBUTION

The literature	Financial incentives have *direct effects* on paid activities and *spillover effects* on unpaid activities, rather than *total* content quantity.	Financial incentives *may not enhance* the quality of user engagement.	Studies anecdotally suggest status can interact with incentives to shape outcomes. However, this variable is not explicitly tested in research.
This study	Measures the effect of paid Q&A on *total content* quantity (the sum of paid answers and free posts), thus considering *both* direct and spillover effects.	Assesses the impact of paid Q&A on user engagement.	Explicitly explores effect of paid Q&A on overall total content quantity and user engagement and the moderating effect of status
Potential contribution	-Identify the *combined effect* of monetization -Test the effects of offering a fee-based feature (paid Q&A) — an IT artifact.	-Identify a financial incentive that enhances user engagement -Offer basis for theorizing the boundary conditions of the effects of monetization -Offer guidelines on how social media platforms engage users.	-Demonstrates monetization interacts with content creator status to shape total content quantity and user engagement.

predict how paid Q&A will affect platform content value. Specifically, it does not clearly predict how paid Q&A will shape overall platform content quantity value, platform engagement value nor how it will incentivize low/moderate status content producers and high-status content producers. Table I presents a summary of the gaps in the literature, and how we propose to fill them.

III. Research Methods

A. Conceptual Development

Expectancy theory proposes that when individuals decide on whether or not to spend effort on a task, they go through a cognitive process of expectancy [58]. Expectancy is the belief that one's effort will lead to the attainment of desired performance [59]. This theory suggests that the expectancy of receiving rewards can encourage individuals to increase their effort in performing tasks and consequently enhance task performance [59], [60], [61]. Research adopting the view finds that content monetization subsidizes users' efforts and motivates them to produce more content [e.g., 20, 62].

Past research on motivation argues that high levels of expectancy increase the amount of effort an individual is willing to expend on task performance and their persistence towards goal attainment [63], [64]. Individuals with high expectancy would be willing to overcome difficult tasks, tolerate a heavy cognitive load, and persist in task performance [65]. The provision of a revenue mechanism heightens the expectancy and motivations of both questioners and answerers [18], [22]. Based on the literature [e.g., 65], we argue that both questioners and answerers would be willing to exert more effort in content generation.

In the context of paid Q&A, the revenue-sharing mechanism guarantees the reward expectancy of all stakeholders [18]. As per expectancy theory [59], all stakeholders (including platforms, questioners, and answerers) are then motivated to exert extra effort in engaging with other users [5] and attracts them to pay for answers [25], [57]. By engaging with other users, answerers will then extend their common practices of posting [5], and exert effort in composing more answers [35]. Hence, we hypothesize the following.

H1: The amount of total content quantity increases after the introduction of paid Q&A.

The literature has also used the concept of flow to conceptualize user engagement [33], [66], [67]. User engagement refers to a heightened state of mind in which people are ready to completely and simultaneously invest their full range of energies in important and meaningful tasks [30]. User engagement is characterized by cognitive absorption [68], focused attention to an experience [69], and heightened enjoyment [33]. The results of user engagement include users' satisfaction with the experience [30], their continuous use of the technology [69], [70], as well as their prosocial activities (e.g., recommending the technology to friends) [29], [30].

The literature suggests that the interactivity of the technology, perceived control, and curiosity (heightened cognitive and sensory curiosity) are antecedents of user engagement [33], [68], [69]. As mentioned previously, paid Q&A enables users to have a high level of control of their content consumption experience, i.e., they can choose to make a micropayment to bypass the waiting time, ask answerers any questions, etc. Paid Q&A can also allow direct interaction with answerers who are celebrities or area experts, people who would otherwise be inaccessible [27]. Also, paid Q&A arouses users' curiosity about the answer to a question [32]. In this sense, the introduction of paid Q&A can enhance the engagement of users on the platform by affording user interactivity, perceived control, and curiosity. Indeed, past literature suggests that introducing a fee-based feature can enhance user engagement in the knowledge-sharing community [29]. Per past literature on user engagement [30], [69], heightened engagement should encourage users to engage in more prosocial activities, i.e., liking and forwarding answerers' content. Thus, we hypothesize the following.

H2: *The number of likes (a) and forwards (b) that an answerer receives increases after the introduction of paid Q&A.*

Furthermore**,** the literature suggests individuals of low status tend to exhibit status-seeking behavior on social media platforms [36], [71]. They seek status by actively participating in and contributing to the community [51], [71]. Definitely, the desire for status directly motivates individuals to answer more questions and exert effort [35], [51], [57].

In the context of paid Q&A, to receive more paid questions, moderate-status answerers are motivated to seek high status [35], [51], [57]. Moderate status answerers can achieve a high status in the community by making contributions such as posting free content [51] or helping others [35]. Therefore, with the introduction of the paid Q&A feature, answerers of moderate status will more likely exhibit status-seeking behavior (e.g., by actively contributing to the community) than those of high status. We expect that moderate status answerers will be more active than answerers of high status in terms of overall content generation after the introduction of paid Q&A feature.

H3: *An answerer's status negatively moderates the impact of the introduction of paid Q&A on total content quantity produced. In other words, high status answerers are less likely to produce more content when paid than answerers of lower status.*

On the other hand, answerers of high status tend to be more protective of their reputation [72]. Paid Q&A allows producers to leverage intellectual capital and social capital to obtain economic capital [36]. Such capitalization can hurt their status [70]. To offset the risk of status damage, producers more carefully manage their production by only providing high-quality content [36]. In addition, the literature suggests people of high status are more cautious with their behavior [73] and prefer to contribute high-quality content to avoid any status damage [72]. In other words, answerers of high status are likely to generate high-quality content in the presence of the paid Q&A feature. Conversely, with the introduction of paid Q&A, answerers of moderate status need to divide their energies to build up their reputation [35] and produce more answers to attract attention. Such increased production could be at the expense of quality. Thus, we expect the following.

H4: *An answerer's status positively moderates the impact of the introduction of paid Q&A on the number of likes (a) and forwards (b) that an answerer receives. In other words, high status answerers obtain more likes and forwards of their new posts than answerers of lower status.*

B. Institutional Details and Data

We study paid Q&A on Weibo, one of the largest social media platforms [74]. It had 462 million monthly active users and 200 million daily active users in December 2019 [75]. The Weibo platform affords users the ability to post, share, and evaluate content in their social network. Such content includes news, original posts, articles, photos, music, and videos. Except for paid Q&A, all content on Weibo is free. Weibo also allows broadcasting and private communication. Users can follow (or be followed by) other users. They can interact by liking or forwarding each other's posts. Liking and forwarding are the two important user engagement functions Weibo affords [76]. Given its large user base and that its features are similar to other social media platforms, Weibo can be reasonably considered a typical social media platform. Moreover, Weibo.com affords a community for user content generation and engagement and relies on such content for survival [17].

The Weibo paid Q&A feature was launched on December 16, 2016, providing a natural experiment investigating the impacts of paid Q&A adoption [77]. The launch was broadcasted to all Weibo users that day [78], and no prior announcement was made. Users did not know about the system change beforehand. The screenshots of the Q&A feature and a translation are depicted, as Figs. 2 and 3 in the Appendix, respectively.

C. Study Procedure

We collected data from Weibo.com from June 1, 2016 to June 30, 2017. We use the launch of the paid Q&A feature on Weibo as an exogenous shock to platform users in terms of system changes as per prior literature [e.g., 29, 79]. The period from June 1 to November 30, 2016, is the pretreatment stage, as the Q&A feature did not then exist, and the period from January 1 to June 30, 2017, is the post-treatment stage. We excluded data from December 1–31, 2016, to rule out the effects of adoption dynamics—seeing that paid Q&A was introduced on December 16. Other studies use a similar-sized or narrower time window [e.g., 17, 29]. Lee et al. [80] suggested that on social media, the disruptive impacts of an exogenous shock dissipate within 15 days or less. Therefore, one month should be enough. We obtained a list of users who adopted the paid Q&A service in the first week of its launch and registered an account on Weibo no later than January 1, 2016. The number of users in this treatment group during this period was 202. We then collected panel data for the treatment group users. For the control group, we used coarsened exact matching to identify 202 similar users who did not adopt Weibo Q&A prior to July 1, 2017, to reduce self-selection bias.

CEM is useful to help identify causality from observational data [81]. Using this technique, we paired each answerer against a user on Weibo, who did not become an answerer on paid Q&A. The variables used to establish this pairing are platform tenure (years), follower volume, followee volume, gender, location, and job type. We performed a one-to-one match, identifying another group of 202 users who did not adopt the paid Q&A service but were similar in terms of these other variables following Wang et al. [35]. We then employed a DID approach to evaluate the differences between our treatment and control groups [35]. As unmeasured variables outside of this article could have influenced our results, we used user fixed-effects estimation to control for unobserved user characteristics and time fixed-effects estimation to control for time-specific effects.

D. Variables

Total content quantity was measured as the sum of the answerer's posts (free content) and answers to Q&A (paid content) in month t. For Weibo users, these are the only kinds of publicly available content they generate. We measured user engagement using two variables, namely, the average number of forwards and average number of likes that a user received in month t [36].

We denote those users who adopted the paid Q&A feature as the *Paid Q&A* group. If user *i* adopted paid Q&A, then *Paid* $Q\&A_i$ is 1; otherwise 0. We measured the treatment period as *Post-Treatment*$_t$. If the month *t* of user *i* is in the post-treatment period, then *Post-Treatment*$_t$ is 1; otherwise 0. We measured answerer's status with the number of followers the answerer has following Toubia and Stephen [72]. We leveraged previous research to identify confounding variables that can affect our dependent variables. Gender [82], the number of followees [83], [84], and platform tenure [85] were important predictors of user-generated content in prior research and, hence, were included as control variables.[2] We also included month dummy variables from June 1–15, 2017 to control for time-specific effects (*MonthDummy*$_t$). Table V in the Appendix shows the descriptive statistics; Table VI, the variable correlation.

E. Empirical Estimations

We employed the DID approach together with CEM to detect the impacts of adopting the paid Q&A feature, following Wang et al. [35]. The panel data DID regression estimation allows us to take advantage of panel data to control for time and user-specific effects. Our estimation equations for user *i* in month *t* are represented as follows: (1)–(3) shown at the bottom of this page, for $i = 1, 2, \ldots, 202$; and $t = 1, 2, \ldots, 12$. α_i is the user-level random error, and $\mathcal{E}_{it}$ is the user-time level random error, controlling for idiosyncratic effects. Besides our independent and dependent variables, we included control variables in our estimations, which helped us rule out alternative explanations of the effects of the introduction of paid Q&A. The number of followers and number of followees were log-transformed because they naturally form a logarithmic distribution. Most content producers have a small number of followers, but a few have many.

IV. Results

The Hausman test results suggest the fixed-effects model is preferred over the random-effects model ($\chi^2 = 130.01$, $p <$ 0.001). We, thus, performed the DID estimation with panel fixed effects on the matched data. The DID model with panel fixed effects is sufficient to address the endogeneity concerns caused by time-invariant confounders [79].

[2]We only captured the changes in the number of followers and followees after the launch of paid Q&A.

A. Tests of Hypotheses

Table II presents the results of our analysis. The treatment variable Paid Q&A$_i$ is omitted from the analysis because it is time-invariant. The results in Column (1) show that Post-Treatment$_t$ × Paid Q&A$_i$ positively affects the amount of total content produced ($\beta = 4.145$, $p < 0.05$). This finding suggests a user who adopts paid Q&A produces, on average, 4.145 more total content per month compared with a matched user who does not adopt paid Q&A, thus supporting H1. We also tested the impact of paid Q&A adoption on the generation of free content. Column (4) shows that the introduction of paid Q&A decreased the amount of free content. This result is consistent with those in previous studies, i.e., monetary incentives crowd out the generation of free content [24]. The reduction of free content is offset by an increase in paid Q&A content—the total content quantity increases after the introduction of paid Q&A. The increase in paid Q&A exceeds the decrease in free content. In addition, Post-Treatment$_t$ × Paid Q&A$_i$ × Ln(Followers)$_{it}$ negatively affects the amount of total content produced ($\beta = -31.874$, $p < 0.001$). Thus, H3 was supported. Results in Column (2) show under a fixed-effects estimation, Post-Treatment$_t$ × Paid Q&A$_i$ positively affected the average number of forwards a user's posts received ($\beta = 52.478$, $p < 0.001$). A user who adopts paid Q&A receives an additional 52.478 forwards on average compared with the matched user who does not adopt paid Q&A, supporting H2a. The corresponding test of likes in Column (3) shows that answering questions in paid Q&A increases the likes the user receives by 186.827 on average ($p < 0.01$), supporting H2b. Furthermore, Post-Treatment$_t$ × Paid Q&A$_i$ × Ln (Followers)$_{it}$ positively affected the average number of likes ($\beta = 57.926$, $p < 0.001$) and forwards ($\beta = 25.125$, $p < 0.05$) a user's posts received. Thus, H4a and H4b are supported.

$$\begin{aligned}\text{Total\_Content}_{it} &= \beta 0 + \beta 1 \times \text{Paid Q\& A}_i \times \text{Post-Treatment}_t + \beta 2 \times \text{Post-Treatment}_t + \beta 3 \times \text{Paid Q\& A}_i \\ &\quad + \beta 4 \times \text{Platform Tenure}_i + \beta 5 \times \text{Gender}_i + \beta 6 \times log\,(\text{Follower}_{it}) + \beta 7 \times log\ (\text{Followee}_{it}) \\ &\quad + \beta 8 \times \text{Paid Q\& A}_i \times\ \text{Post-Treatment}_t \times log\ (\text{Follower}_{it}) + \sum \text{MonthDummy}_t + \alpha_i + \varepsilon_{it} \qquad (1)\end{aligned}$$

$$\begin{aligned}\text{Average\_Forwards}_{it} &= \beta 0 + \beta 1 \times \text{Paid Q\& A}_i \times\ \text{Post-Treatment}_t + \beta 2 \times \text{Post-Treatment}_t + \beta 3 \times \text{Paid Q\& A}_i \\ &\quad + \beta 4 \times \text{Platform Tenure}_i + \beta 5 \times \text{Gender}_i + \beta 6 \times log\ (\text{Follower}_{it}) + \beta 7 \times log\ (\text{Followee}_{it}) \\ &\quad + \beta 8 \times \text{Paid Q\& A}_i \times\ \text{Post-Treatment}_t \times log\ (\text{Follower}_{it}) + \sum \text{MonthDummy}_t + \alpha_i + \varepsilon_{it} \qquad (2)\end{aligned}$$

$$\begin{aligned}\text{Average\_Likes}_{it} &= \beta 0 + \beta 1 \times \text{Paid Q\& A}_i * \ \text{Post-Treatment}_t + \beta 2 \times \text{Post-Treatment}_t + \beta 3 \times \text{Paid Q\& A}_i \\ &\quad + \beta 4 \times \text{Platform Tenure}_i + \beta 5 \times \text{Gender}_i + \beta 6 \times log\ (\text{Follower}_{it}) + \beta 7 \times log\ (\text{Followee}_{it}) \\ &\quad + \beta 8 \times \text{Paid Q\& A}_i \times\ \text{Post-Treatment}_t \times log\ (\text{Follower}_{it}) + \sum \text{MonthDummy}_t + \alpha_i + \varepsilon_{it} \qquad (3)\end{aligned}$$

TABLE II
DIFFERENCE-IN-DIFFERENCE ANALYSIS OF THE MATCHED SAMPLE

	(1) Total_Content$_{it}$		(2) Average_Forwards$_{it}$		(3) Average_Likes$_{it}$		(4) FreeContent$_{it}$
Post-Treatment$_t$	10.131 *** (0.712)	-0.503 (26.155)	33.976 *** (6.612)	20.087 (57.581)	25.233* (10.069)	3.536 (10.145)	-0.325 (1.257)
Post-Treatment$_t$ × Paid Q&A$_i$	4.145* (2.326)	32.877*** (11.593)	52.478 *** (15.832)	143.344*** (57.172)	186.827 **(15.022)	145.595 ***(45.310)	-8.124* (2.514)
Post-Treatment$_t$ × Paid Q&A$_i$ × Ln(Followers)$_{it}$		-31.874*** (9.203)		57.926*** (19.991)		25.125* (13.522)	-3.561** (0.721)
Ln(Followers)$_{it}$	0.450** (0.141)	0.874 (4.191)	1.687*** (0.235)	10.271 (9.105)	5.678 *** (1.320)	3.232** (1.604)	1.552** (0.671)
Ln(Followees)$_{it}$	0.124 (0.075)	-1.851 (7.065)	1.332 (1.041)	11.337 (15.363)	4.985 (3.023)	0.0918 (2.706)	0.984 (1.314)
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.121	0.128	0.046	0.051	0.176	0.179	0.093
Specification	FE	FE	FE	FE	FE	FE	FE
Obs.	4848						

Notes: Clustered-robust standard errors are reported in parentheses.
*p<0.05; **p<0.01; ***p<0.001

B. Tests of Confound- Parallel Trend Assumption

The DID model has a critical parallel trend assumption that no pretreatment trend exists between the treatment and control groups [79], [86]. We conducted two robustness checks to test whether the parallel trend assumption holds in our study. First, following Angrist and Pischke [86], we conducted the correlated random trend model test. The significance of the estimated effects of interest does not change (all p values < 0.05), demonstrating that our results are not driven by individual-specific time trends.

Second, we conducted the relative time model test suggested by Autor [87] and Khurana et al. [79]. The results in Table VII in the Appendix show no significant effects on our dependent variables in the three months before the introduction of paid Q&A but sharp increases in effects on our dependent variables are noted after the introduction of paid Q&A. Interestingly, we found no effect in the first month after treatment on the average likes but a significant effect on the second month after treatment. This result suggests that it takes around 1–2 months for the introduction of paid Q&A to translate into higher average likes. These results show no sign of pretreatment trends in our study, providing further support to the robustness of our findings. The help us rule out the potential influence caused by time-variant unobservable confounders [79].

C. Test of Confound-Placebo Test

Following Khurana et al. [79], we also conducted a placebo test to examine whether our results may be caused by the Hawthorne or novelty effects. We randomly selected half the users in the sample and assigned them as the treatment group (placebo treatment), but the values of dependent variables (i.e., total content, and average forwards and likes) remained the same. We then reran the fixed effect DID estimation for each dependent variable to see whether the placebo treatment would significantly affect our dependent variables. We repeated this process 1000 times. We found hypothesis support for total content 25 times, average forwards 12 times, and average likes 19 times, all of which are lower than 50 times, i.e., a 5% chance of rejecting the null hypothesis. The averaged coefficients of the placebo treatment on total content averaged forwards and likes from the 1000 estimations are 0.641, 1.842, and 10.670, respectively, which are much lower than the coefficients shown in Table II. Therefore, our results are not driven by the placebo effect, ruling out the alternative explanation of the Hawthorne and novelty effects.

D. Test of Confound-Instrument Variable Estimation

One possible confounder to our results is the presence of endogeneity issues. We performed the Lewbel [88] test to determine the causal effects in our model. Lewbel [88] test measured the effect of unobservable variables that can confound the effects in our study. Lewbel [88] mathematically constructed instruments from covariates specified as exogenous. The Lewbel test treats all variables except our independent variables of interest as exogenous to the dependent variable. Results of this test are presented in Table III.The p-value of the Hansen J statistic is higher than 0.05, suggesting no evidence of an over-identification issue. Results in Table III remain the same as those in Table II. This result adds further support to the robustness of our research findings.

V. DISCUSSION

Social media platforms have begun experimenting with using monetization to encourage content generation [89]. Practitioners and researchers are eager to understand the impact of monetization on content generation [20] and user engagement [29]. This article asks a fundamental question about the impacts of paid Q&A—a nascent monetization model—on platform value

TABLE III
IV REGRESSION USING GENERATED INSTRUMENTS

	DV= Total_Content$_{it}$	DV= Average_Forwards$_{it}$	DV= Average_Likes$_{it}$
Post-Treatment$_t$	4.201*** (1.245)	210.123** (90.045)	51.023* (23.453)
Post-Treatment$_t$ × Paid Q&A$_i$	18.471* (9.040)	562.223** (220.023)	224.374***(30.445)
Post-Treatment$_t$ × Paid Q&A$_i$ × Ln(Followers)$_{it}$	-15.364*** (3.265)	31.698*** (5.236)	20.258* (8.154)
Control Variables	Yes	Yes	Yes
Monthly Dummies	Yes	Yes	Yes
R-square	0.119	0.255	0.141
Cragg Donald Wald F-Stats	10.26***	6.32***	58.12**
Hansen J (p-value)	6.132 (0.075)	5.11(0.055)	7.921(0.071)
Observations	4848		

Notes: Clustered-robust standard errors are reported in parentheses.
*p<0.05; **p<0.01; ***p<0.001

in terms of total content quantity and user engagement. We hypothesized the combined effects of the introduction of paid Q&A on platform value and explored the moderating effects of status on the combined effects. We then used unique panel data from Weibo to test the hypotheses via a natural quasi-experiment. Our findings show that the introduction of paid Q&A increases total content quantity and the number of forwards and likes received on average, suggesting that paid Q&A can improve platform value. Answerers of low or moderate status benefit more from paid Q&A in terms of increased total content quantity whereas answerers of high status benefit more from paid Q&A in terms of enhanced user engagement.

A. Theoretical Implications

Our findings contribute to the existing literature in several ways. First, our study finds that paid Q&A is an effective monetization model that encourages users to generate a greater amount of and more engaging content. It adds to the paid Q&A literature [e.g., 18, 25, 27] by delineating and quantifying the combined effects of introducing the paid Q&A feature on platform value. Such a focus offers a more holistic understanding of the impacts of monetization on the total content quantity rather than the separate effects on paid or unpaid activities. Thus, this article advances our understanding of the strategic importance of paid Q&A and specific benefits that it can bring to the host platform.

Second, existing knowledge in prior literature [e.g., 16, 20] posits that monetary incentives may not change the quality of user-generated content. This article finds that such an introduction brings in more forwards and likes per month. Thus, our findings are novel and advance our understanding of monetization. In other words, this article advances our understanding of how user engagement varies with a system change.

Third, our study adds to the literature on how technology can enable monetization [5], [21] by identifying a new technology-enabled business model that enables user engagement. For paid Q&A to work, there must be an underlying technology infrastructure supporting it, and this new technology infrastructure and the concomitant business model has only arisen recently (i.e., within the past five years). For example, one needs technology to display the question while blocking the answer and set up the paywall.

To our knowledge, no prior study has found a monetization model that increases the quality of online content [20], [40], [90]. In addition, our study extends the application of expectancy theory to a new context, i.e., paid Q&A. It further develops expectancy theory by integrating the status seeking research to identify the boundary condition altering the effects of a new technology-enabled monetization on total content quantity. In a similar vein, this article develops user engagement research by integrating status-seeking research to offer a more nuanced understanding of the effects of monetization on user engagement.

Fourth, this article reveals an important boundary condition altering the effects of monetization. Specifically, it identifies the moderating effects of answerer status on the impacts of introducing a new technology-enabled monetization model. The existing literature [e.g., 29, 57] has not explicitly studied whether individuals on social media are equally motivated by monetization. This article explores the contingency of the impacts of introducing a paid Q&A feature. It finds that answerers of high status benefit more from the paid Q&A feature in terms of enhanced user engagement whereas answerers of low or moderate status benefit more in terms of enhanced total content quantity. Our findings advance our understanding of the boundary condition of technology-enabled monetization and extend prior research [e.g., 19, 35] by showing the limits of monetization.

B. Managerial Implications

Our work offers managerial insights for social media platforms debating the appropriateness of introducing a monetization model to their users and the investment decisions on implementing a fee-based feature. First, our results suggest that the introduction of paid Q&A provides opportunities to enhance platform value by encouraging the production of more content and facilitating user engagement. Design features that support paid Q&A are important. Most social media platforms incentivize content generation via an ad-revenue model [17]. The problem with this model is that content producers do not receive direct feedback on the kind of content their audience wants. Paid

Q&A provides such feedback ex-ante—a questioner asks for specific kinds of content to be produced. Given the questioner benefits if the answer is viewed, the questioner signals to the answerer that the answer is valued by a wide audience. The success of paid Q&A suggests social media platforms should design such feedback mechanisms to better direct content producers to develop not only content, but content their audience wants to consume.

Second, with other technology-mediated monetization, e.g., paywall or freemium [5], [29], [91], paid Q&A allows answerers and questioners to interact [55]. This interaction better embeds them into the platform. This suggests that social media platforms should provide a virtual space (e.g., paid Q&A) for interactivity among participants so that all users get involved in cocreating more engaging content. Third, rather than viewing every answerer as being equally incentivized, paid Q&A motivates answerers of low status to contribute more content and gradually build up their status on the platform. Our research indicates that the effects of the paid Q&A model spill over to induce status seeking behavior for answerers. Such status seeking is helpful for platform viability [36]. Furthermore, answerers of high status tend to produce content of high quality with the presence of a paid Q&A model. This finding suggests that social media platform should encourage answerers of high status to increase their content production for platform viability.

VI. Conclusion

This article explores the impact of paid Q&A on the total platform value of the social media platform Weibo. We find paid Q&A increases total platform value by increasing both the quantity of total content generated and the quality of aforesaid content as measured by user engagement. Our research also finds a moderating effect of the introduction of this feature. Specifically, higher status users are more conservative in answering questions posed to them, but when they do answer, they generate answers of better quality.

Our findings should be interpreted in terms of their limitations. Our research model is derived from and tested on Weibo Q&A, a single platform with a specific type of paid content. In Weibo Q&A, it vets the qualification answerers. Vetting the qualification of content production or controlling the access to monetization is one of strategic platform input controls to make sure that content of inferior quality will not flood the platform and crowd out high-quality content [92]. Such vetting will indeed affect the quality of content generated [4], [26]. Our findings may be generalizable to platforms who have similar fee-based features and qualification vetting, such as seeking Alpha, Fenda.com, and Zhihu.com [18], [29], [35]. Further research on other types of paid content platforms is needed to test the generalizability of our findings. Our data were collected in China, a country with numerous unique characteristics. For example, online communication is highly regulated, which can affect individuals' online behaviors. Future research on multiple countries is necessary for ruling out the idiosyncratic features of China on our results.

Future research can be done using textual or other qualitative analyses of the actual Q&A questions and responses to identify nuances in relationships our study misses. For example, our research finds that paid Q&A has different impacts on the accrual of content quantity value and user engagement value across high and moderate status content producers. However, while we posited a reason, we cannot guarantee our explanation is correct. A content analysis comparing what high and moderate status content producers generate may answer this question. Another direction for future research is a qualitative analysis of the actual Q&As to determine what makes content desirable to answerers and consumers of content. Also, future research can identify appropriate instrument variables and test if our findings hold.

Furthermore, we aggregated free and paid content to construct the measure for our dependent variables. We acknowledge that free content differs from paid content in terms of generation motivation, content type, and content quality. Future research can compare the differences between the two types of content and examine how the introduction of paid Q&A affects the quantity and quality value of free content. Doing so can provide a more nuanced understanding of the impacts of introducing paid Q&A.

Appendix

Fig. 2. Screenshot of answerers' list.

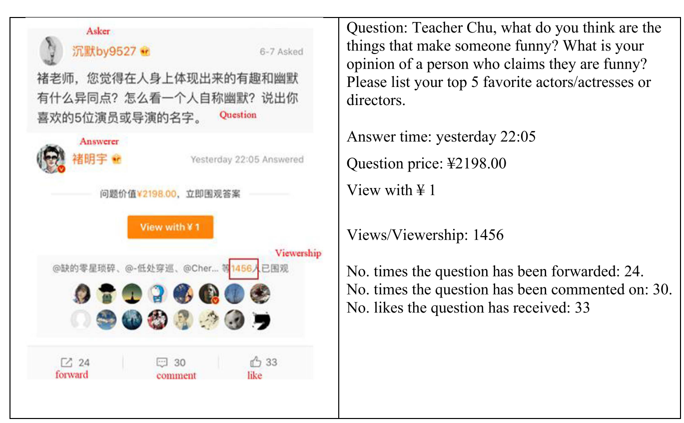

Fig. 3. Screenshot of A Q&A Page.

TABLE IV
REVIEW OF EMPIRICAL FINDINGS ON THE IMPACTS OF MONETIZATION

Theme	Reference: Context	Findings
Offering financial incentives	Qiao et al. [24]: Receiving financial incentive for review writing in Amazon	Spillover effect: Receiving financial incentives leads to reduced effort, biased sentiment, and lower quantity in subsequent **free** contributions.
	Khern-am-nuai et al. [40]: Receiving financial incentive for review writing	Direct effect: monetary incentives lead to more **paid** reviews, which is biased with positive sentiments and shorter.
	Burtch et al. [93]: Experiments of offering financial incentives in review writing	Direct effect: monetary incentives can induce more customers to provide the **sponsored** review but do not increase review length.
	Burtch et al. [19]: field experiment of offering peer awards to user generated content	Direct effect: peer award induces the generation of longer and more frequent **free** posts. However, peer award leads to the generation of similar rather than novel content.
Introducing a fee-based feature	Kuang et al. [29]: Zhihu paid live talk	Spillover effect: The introduction of paid live session increases users' **free** knowledge sharing volume.
	Chen et al. [16]: premium partnership program	Direct effect: the introduction of premium partnership program on stock article writing increases contributors' **paid** content output quantity and wider stock coverage but not the quality of stock recommendation.
	Wang et al. [35]: Zhihu paid live talk	Spillover effect: The introduction of paid feature increases hosts' contributions of more and longer **free** answers but not the quality of answers (number of upvotes).
	Tang et al. [22]: Revenue sharing program on YouTube	Direct effect: revenue-sharing program can induce the generation of more **free** videos on YouTube.
Introducing the paid Q&A feature	Lin and Huang [94]: Comparing Google Answers (paid Q&A) with Yahoo! Kimo Knowledge+ (free Q&A)	Direct effect: Google Answers fails with its paid feature, but Knowledge+ succeeds with its virtual rewarding mechanism.
	Hsieh et al. [95]: A field study of Mahalo Answers	Direct effect: Paying induces a higher number of **paid** answers and answers of greater length but may not elicit higher quality answers.
	This study: A natural quasi-experiment on Weibo Q&A	**Direct and spillover effects:** (1) introducing paid Q&A induces an increase in the overall content (the sum of paid and unpaid content) (2) introducing paid Q&A leads to an increase in the quality of overall content (likes and forwards) **Contingencies:** Answerers' status positively moderates its impact on overall content but negatively on content quality.

TABLE V
DESCRIPTIVE STATISTICS OF USERS IN TREATMENT AND CONTROL GROUPS

	Treatment Group		Matched Control Group		
	Obs	Mean	Obs	Mean	Differences (p-value)
$Total\_Content_{it}$ (ex-ante)	1212	42.28	1212	40.56	1.72
$Total\_Content_{it}$ (ex-post)	1212	50.10	1212	42.30	7.80**
$Average\_Forwards_{it}$ (ex-ante)	1212	242.04	1212	200.76	41.28
$Average\_Forwards_{it}$ (ex-post)	1212	339.39	1212	224.69	114.7***
$Average\_Likes_{it}$ (ex-ante)	1212	140.26	1212	102.77	37.49
$Average\_Likes_{it}$ (ex-post)	1212	348.36	1212	121.88	226.48***
Gender	2424	0.52	2424	0.54	0.02
Platform Tenure	2424	6.11	2424	5.95	0.16
Followers (ex-ante)	1212	195541.32	1212	196128.61	587.31
Followers (ex-post)	1212	197815.02	1212	196361.21	1453.81*
Followees (ex-ante)	1212	3689.45	1212	3491.03	198.42
Followees (ex-post)	1212	3745.02	1212	3521.63	223.39

*p<0.05; **p<0.01; ***p<0.001

TABLE VI
CORRELATION MATRIX

	1	2	3	4	5	6	7	8	9
1.Total_Content	1								
2.Average_Forwards	0.18	1							
3.Average_Likes	0.30	0.48	1						
4.Paid Q&A	0.11	0.02	0.22	1					
5.Post-treatment	0.05	0.02	0.19	-0.41	1				
6.Gender	-0.10	-0.01	0.10	-0.35	0.16	1			
7.Platform Tenure	0.01	-0.01	0.01	-0.08	0.19	0.18	1		
8.Followers	0.11	0.14	0.13	0.01	0.02	0.03	0.11	1	
9.Followees	0.15	0.02	0.01	0.05	0.01	0.05	0.01	0.11	1

TABLE VII
PARALLEL TREND TEST USING THE RELATIVE TIME MODEL

	$Total\_Content_{it}$	$Average\_Forwards_{it}$	$Average\_Likes_{it}$
Lead 3 (Sep-2016) * Treatment	0.887 (0.940)	-31.454 (33.862)	-9.988 (20.494)
Lead2 (Oct-2016) * Treatment	1.857 (1.141)	6.375 (8.728)	5.560 (5.721)
Lead1 (Nov-2016) * Treatment	1.449 (2.026)	7.722 (6.777)	2.514 (3.506)
Lag1(Jan-2017) * Treatment	4.718** (1.126)	3.317* (1.616)	5.041 (11.026)
Lag2 (Feb-2017) * Treatment	22.699*** (4.180)	75.751*** (14.939)	35.560*** (5.257)
Within Panel R-squared	0.053	0.004	0.039
Controls	Yes		
Individual FE	Yes		
Observations	4848		

Results on control variables and fixed effects are omitted for simplicity. Standard errors are clustered at the individual level. *p<0.05; **p<0.01; ***p<0.001.

ACKNOWLEDGMENT

The authors would like to thank the department Editor, Dr. D. Cetindamar, and two anonymous reviewers for the constructive comments and guidance.

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