Monetizing User-Generated Content in FinTech: An Empirical Study of a Social Investing Site

Research-in-Progress

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Abstract

Despite reports that user-generated content (UGC) is dominating the Internet, the contributors of UGC are rarely compensated for their creative works. Enabled by a unique dataset from a large social investing site in China, we conduct an empirical study to examine the UGC monetization in terms of its influence, the timing of a contributor’s adoption and the impact from online social activities. Our analyses utilize multiple methods (time-series modeling, logit modeling and Bayesian statistical analysis). Our contributions include: 1) This study is the first to unveil the impact of UGC monetization on the platform and contributors with a horizontal comparison of different monetization methods; 2) We make a pioneering effort to analyze how contributors’ online social efforts (i.e., the micro-celebrity tactics) facilitate monetization; 3) Our results advance the financial information literature by showing how UGC readers seek information; 4) Our results inform practitioners how to time the decision of monetization.

Keywords: User-Generated Content, Monetization, Micro Celebrity, Social Investing Site, FinTech, Financial Information Market, Bayesian Estimation
Introduction

User-generated content (UGC) is dominating the Internet (Meeker 2015). However, the contributors are seldom compensated for their efforts or creative works (Terada et al. 2013). Despite the arguments that some contributors are motivated by social incentives, such as attention, peer recognition, and reputation (McWilliam 2012; Ovier 1999; Shen et al. 2015), these arguments do not necessarily hold for all, especially for the kind of work that demands more deliberate endeavors, time investments and generates much economic value. Some even lament that un(der)paid contributors are a type of slave labors and detrimental to the sustainability of UGC production (Kleemann et al. 2008; Morphy 2009).

Consequently, some UGC monetization methods have been proposed and implemented to incentivize and remunerate the contributors. These methods can be categorized into: direct monetization and indirect monetization. Direct monetization includes charging readers for accessing and receiving rewards given by readers. Indirect monetization includes advertisements-attached content, commissions from the platform and commissions from e-commerce sites (known as affiliate marketing, see (Duffy 2005)). But no method is perfect: its strengths have to be weighed against its weaknesses. For example, although indirect monetization may demand little economic burdens to the readers, it actually requires an enormous amount of web traffic to cover the operating cost. As another example, although some direct monetization methods can bring immediate revenue, it may deter potential readers who are uncertain about the quality of the content, an information asymmetry problem leading to a “lemons market” (Akerlof 1995).

Albeit there are a number of designs in practice (Gaedcke 2006; Klinger and Wada 2008; Navarro et al. 2009) and in literature (Terada et al. 2013) about monetizing UGC, surprisingly, to the best of our knowledge, no empirical study has examined this important issue, especially in terms of the horizontal comparison of different monetization methods. To fill this void, we focus on three issues in UGC monetization: namely its influence on the platform, the timing of a contributor’s adoption of UGC monetization and how it is influenced by online social activities.

The three issues are critical for the following reasons. Firstly, the economic benefits of the UGC may come at the expense of a reduced reader base. Whether this loss is bearable to the platform is worthy of a thorough study. Secondly, timing is the key to success (Schilling 2002). Individual contributors should acquire a position of importance or influence in the platform before adopting UGC monetization. It is equally important for contributors to time the UGC monetization in an advantageous macro environment. Lastly, UGC is, and increasingly will be, produced in online social settings (Meeker 2015). To what extent contributors’ online social activities further the UGC monetization should receive a closer examination.

Noteworthy, UGC contributors may end up being “micro-celebrities” (Senn 2008), a term coined to refer to the online user who engages himself/herself in self-presentation and self-branding to develop and maintain an audience (Hearn 2008; Lair et al. 2005). This is made possible by the advancement and capability of social media, which brings about an enormous amount of content creation and circulation. By strategically addressing and interacting with fans and followers, micro-celebrities present an image of intimacy, authenticity, authority and expertise to maintain their popularity. Yet, their arduous effort and tactics have never been quantified into economic value. Hence, this study raises three research questions:

RQ 1: How does monetization of user-generated content (UGC) affect the platform, in terms of web traffic?
RQ 2: How does the timing of a contributor’s adoption of UGC monetization, in terms of his/her position in a social network and the macro market condition, influence the success of the adoption?
RQ 3: How do the micro-celebrity tactics of a contributor influence the economic value of his/her UGC monetization?

To address these three research questions, we draw on the context of social investing sites (SIS), a form of “Financial technology” or “FinTech” (Arner et al. 2015), whose mission is to disrupt and innovate the financial information market by exploiting the “Wisdom of Crowds” (Chen et al. 2014). For decades, the financial information market is dominated by a small number of brokerage firms and investment banks, such as Merrill Lynch and Goldman Sachs. Information is the most sought after and valuable product in the financial world. Two types of information products are offered to investors: research (e.g., stock history, investment advice, opinions and analyses, etc.) and execution (e.g., quote, volume, and bid/ask prices, etc.) (Raghunathan and Sarkar 2016). However, this landscape has been dramatically
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revolutionized to embrace more diverse sources of information, in the form of independent analysts and retail investors contributed content (SEC 2012). Cogent Research (2008) reports that almost one fourth of U.S. investors directly depend on investment advices disseminated through online social media channels. SIS, in particular, is exclusively dedicated to the discussion of stock markets. For instance, StockTwits, a U.S.-based SIS, currently hosts 40 million users, doubling the number from two-years ago.

As a pilot study, we intend to gather and analyze our primary data from iMaibo, a large SIS located in China, which hosts 3 million registered users. Among them, 600 have applied to monetize their UGC. Three forms of UGC monetization were enabled in May 2014: 1) VIP-based access, in which the content is only accessible to paid subscribers; 2) IP subsidy, in which iMaibo pays the respective contributors monthly based on their viewership; 3) Virtual gifts, which followers voluntarily purchase to reward contributors. We intend to analyze data from January 1, 2013 to May 1, 2016 (i.e., both pre- and post-monetization of UGC), including those of UGC (e.g., tweets, blogs) together with comments and retweets, the daily operating statistics of iMaibo (e.g., number of visits, likes, posts), the transaction history of the three monetization methods, the following and/or subscription activities of all users, the demographic information of users and UGC contributors, etc.

We intend to adopt multiple empirical analysis methods to analyze our data both at the platform level and at the individual contributor level. A time-series modeling approach will be employed to examine the influence of UGC monetization on the platform. A binary logit model will be used to investigate how to time the decision of UGC monetization to ensure success. Also, we will use a Bayesian statistical modeling approach to examine the impact of the micro-celebrity tactics on the economic value of UGC monetization.

Our study has the potential to make the following critical contributions: 1) This paper is one of the first studies that inquire into the influence of UGC monetization on a social-network based platform and its contributors as well as horizontally compare different monetization methods; 2) It is also a pioneering effort to analyze how contributors’ online social efforts, i.e. the micro-celebrity tactics, can facilitate UGC monetization; 3) Our results advance the financial information literature by showing how investors (i.e., readers) seek and consume such information. 4) Pertinent to practitioners, our results will shed light on how to time the decision of UGC monetization and to improve content management on UGC websites.

Literature Review

Two streams of literature are relevant: namely, research on monetization of user-generated content and research on micro-celebrities.

Monetization of Use-Generated Content (UGC)

Extant works on UGC monetization is predominantly focused on the design of systems and the monetary incentives.

Both direct and indirect monetization methods have been proposed to incentivize and remunerate UGC contributors. Three indirect UGC monetization methods prevail. The first method is advertisements (Krishnamurthy and Dou 2008), which the contributors and the platform can associate with the produced content. The second method is affiliate marketing (Duffy 2005), in which the contributors can write recommendations about products and link it to online stores (e.g., Amazon) to get commission fees based on the number of referrals. Both the first and second methods are challenging by placing a huge demand on web traffic to cover operating costs. In general, followers tend to be annoyed by advertisements, and even more so if they are irrelevant (Cisneros 2003). The problem is compounded when increasingly, ad-blocking techniques are adopted (The Economist 2012). The third method is commissions paid by the platform to contributors on platforms such as YouTube (Nelson 2013).

Another natural direct UGC monetization is simply to charge readers for accessing the content. However, a “lemons market” (Akerlof 1995) information asymmetry problem arises. Since potential readers have no

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1 VIP refers to “very important person”, i.e., the users who pay the subscription fees to contributors.

2 IP is Internet Protocol address, i.e., the number of unique viewers that a UGC contributor can attract.
guarantee of UGC quality, they may be deterred, especially given that some opportunistic contributors may exploit information asymmetry to produce lower quality content. As a result, researchers have proposed a number of approaches to alleviate this risk for readers, such as preview, reputation system (Yamagishi and Matsuda 2002) and micro-billing scheme (Terada et al. 2013). Yet, the risk for UGC contributors and the platform still exists, because fee-charging for content access can shun away less willing-to-pay readers and reduce the overall traffic and content participation rate.

A recent interesting practice of direct UGC monetization is virtual gifting, evident in the “fan economy” (WSJ 2015). For example, in YY.com, a Chinese video-streaming site, a user can buy amateur artistes virtual gifts to reward their performance. Although such gifting actions are totally voluntary, top performers can amazingly earn as much as US$161,000 per year (WSJ 2015). This is however not an easy feat because an ultra-high hedonic or utilitarian value and interactive communication capabilities are needed before such returns to UGC monetization are possible.

Our study is related to the literature about monetary incentives on UGC activities, in which the effect of such incentives on content quality, length, usefulness, credibility and participation level have been studied (Becker et al. 2010; Chen et al. 2010; Hsieh et al. 2010; Khern-am-nuai and Kannan 2014; Liu et al. 2014; Liu and Feng 2015; Mason and Watts 2010; Wang et al. 2012). However, there has been no empirical study that examines the economic value of UGC monetization as accrued to the UGC contributors, especially on how monetization timing and social interactions influence such economic value.

To address the above research gaps, our study will examine and compare the economic values of different UGC monetization methods as well as monetization timing and UGC contributors' micro-celebrity tactics.

**Micro-Celebrities**

This literature review also draws insights about the various micro-celebrity tactics that UGC contributors exploit to facilitate the monetization of their generated content.

The emergence of social media sites has transformed *celebrity* from "an inborn trait" to "a learned practice" (Marwick 2011). Common online users can adopt the tactics used by real "celebrities" to gain popularity, to achieve status and to portray an image, with examples being camgirls (Senft 2008), technology entrepreneurs on Twitter (Marwick 2011) and amateur performers in YouTube (Burgess and Green 2013). This group of online celebrities is coined "micro-celebrity" by Senft (2008) to connote their popularity over the Internet using videos, blogs and social network sites. They engage in a "participatory culture" by relying on social media to produce their own cultural products (Jenkins 2006; Lessig 2004).

Micro-celebrity practices include the use of a variety of techniques to construct identity among followers, to treat them as an aggregated fan base, in order to obtain social or economic benefits (Marwick 2011; Page 2012). Empirical findings show that visibility, affiliation, and endorsements are the core tactics that micro-celebrities exercise to accrue status and perceived influence. Since textual content is the main type of content for UGC creation and circulation in our study, we focus on the literature about micro-celebrities’ strategic use of linguistic and website components. First, efforts in enhancing visibility are numerous. In social media sites, hashtag (i.e. #) is used to indicate a searchable term and topic, and indeed # has helped enhance the visibility of tweets (Page 2012). In SIS, the dollar symbol (i.e., $) is assigned the functionality of locating a specific stock. The stock portal will then aggregate all the tweets that mention this specific stock using $. Similar to #, UGC contributors in SIS may strategically comment on hot stocks using $, so as to increase the visibility of their content. Also in SIS, contributors can self-recommend their tweets or blogs to the platform editors, which may be broadcast to all users. This self-recommendation is yet another conscientious effort to increase visibility.

Second, affiliation is the practice that micro-celebrities treat their followers as one collective group rather than individuals, which is often used to enhance intimacy, powerful differences and perceived influence (Page 2012). Such affiliation practices include 1) “collective referring”, which means addressing followers as a collective nouns, such as “we”, “guys” rather than individual names or not referring at all; 2) “asking the crowds” (Zappavigna 2011), in which micro-celebrities post a question to their followers to encourage participations; 3) “demanding actions” that often urge contributors to encourage followers to undertake certain actions, such as “liking” their content.
Third, micro-celebrities also strategically reflect endorsements from fans, which is often done via public acknowledgement using retweets. To do so, micro-celebrities may intentionally retweet a follower’s gratitude or praise to highlight the existence of satisfied consumers of their content. Alternatively, micro-celebrities may choose to publicize their comments or replies to their followers’ opinions or questions (Marwick 2011), which is often being commended openly, so that their worth is being celebrated.

Although visibility, affiliation and endorsement have been identified as possible ways for UGC contributors to offset potential negative effects (e.g., losing followers, web traffic) of UGC monetization, prior studies tend to be qualitative in methodology and have not quantified the economic values of doing so. Armed with text-mining techniques (Feldman and Sanger 2007), our study tries to quantitatively examine the impact of the three micro-celebrity tactics on the economic values of UGC monetization.

**Methodology**

**Research Context and Data Collection**

We seek to examine our research questions using data from iMaibo, a China-based SIS. Founded in 2011, iMaibo adopts a Twitter-like structure in which users are able to follow one another to buzz about the flux of stocks in real-time news feeds. iMaibo introduced the UGC monetization scheme in May 2014, allowing users to apply to be a financial “expert” contributor. Once approved, users can monetize the content that they have produced. The scheme classifies all users into two groups: financial experts (referred to as UGC contributors in this study) and retail/individual investors (referred to as UGC readers in this study, although they can generate free or unremunerated content too). iMaibo hosts 3 million registered users as of May 1, 2016. Among them, 600 are UGC contributors. Figure 1 shows the conceptual relationship among all users and the UGC monetization scheme in iMaibo.

![Figure 1. Conceptual Relationships in Social Investing Sites (SIS)](image)

There are three methods for UGC contributors to monetize their content: paid subscription, virtual gift and IP subsidy. In iMaibo, UGC contributors offer financial information (e.g., instructions, advices, analyses, stock news, etc.) to readers in the form of tweets, blogs. The information can be free, accessible to all, or paid, that is accessible only to subscribed readers (known as VIP content). UGC readers are able to follow contributors freely to get the public content, subscribe them to access the VIP content, as well as reward them with virtual gifts on their own will. At the same time, contributors can get IP subsidy from the platform monthly, whose amount is based on the number of unique readers that contributors can attract during one month, to compensate for their contribution to the platform’s web traffic.

We intend to analyze various aspects of the data from iMaibo. For example, the data detailing daily operation statistics of iMaibo (such as the number of visits, total posts, total comments, etc.) will help answer how UGC monetization influences web traffic. Also, we intend to analyze all contributors’ and readers’ data (such as demographic data, posts/comments identified by user identifier and timestamp, trading records of VIP subscription, virtual gifts, and IP subsidy, etc.) using text-mining techniques, to help determine the occurrence and influence of the three micro-celebrity tactics. With machine learning techniques, we can compute the sentiment of UGC generated. Sentiment is consistently utilized to gauge how much the buzz in social media sites (Bollen et al. 2011; Sprenger et al. 2014) and SIS (Nasseri et al.
The unit of analysis is at the individual contributor level. It is measured by the number of visits to the platform on day \( t \). \( \text{user}_\text{base} \) is the total number of registered users on day \( t \). \( \text{num}_\text{vip} \) represents the number of contributors adopting the monetization method of VIP content on day \( t \). Similarly, \( \text{num}_\text{gift} \) and \( \text{num}_\text{ip} \) measure the numbers of contributors adopting the method of virtual gift and IP subsidy respectively.

The Impact of the Timing on the Adoption Success of UGC Monetization

We use two variables to study the timing of the adoption of UGC monetization, i.e., the position of a contributor in the social network of the platform and the market's condition. To examine how the timing of a contributor's adopting the UGC monetization influences the success of adoption, we specify the following panel-level logit model,

\[
\logit(sc_{it} = 1) = \beta_0 + \sum_{j=1}^{n} \beta_{1,j} \text{num}_\text{pos}_{ij,t} + \sum_{j=1}^{n} \beta_{2,j} \text{num}_\text{vip}_{it} + \sum_{j=1}^{n} \sum_{m=1}^{n} \beta_{3,j,m} \text{num}_\text{pos}_{ij,m} \times \text{num}_\text{vip}_{im,t} + \sum_{k=1}^{n} \beta_{4,k} \text{mon}_\text{type}_{ik,t} + \beta_{5,\text{control}}
\]

The unit of analysis is at the individual contributor-month level. \( i \) and \( t \) are the individual and month subscripts respectively. The dependent variable, \( sc_{it} \), indicates whether a UGC contributor has adopted the monetization method.
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successfully obtained a revenue above US $200\textsuperscript{3} per month from his monetization method, with $sc_{i,t} = 1$ denoting success. $ntk_{pos,i,t}$ represents the position of contributor $i$ in the entire network at month $t$. $m$ indexes the four centrality variables (Wasserman and Faust 1994) that we use to measure the network position ($m=1,2,3,4$ represent in-degree centrality, out-degree centrality, authority centrality and hub centrality respectively). $mrk_{cdn}_{i,t}$ denotes the market conditions at month $t$ for contributor $i$. $p$ indicates the two market condition variables, trade volume ($mrk_{cdn}_{i,1,t}$) and market volatility ($mrk_{cdn}_{i,2,t}$). According to Dzielski (2012) and Vlastakis and Markellos (2012), investors’ information demand is positively associated with trade volume and market volatility. Thus different market conditions may lend UGC contributors advantages or disadvantages to start monetizing their content. We also investigate the interaction effect of the position in the social network and the market condition, which is captured by $ntk_{pos,i,t} \times mrk_{cdn}_{i,t}$. $mon_{type}_{i,k,t}$ is a set of dummies indicating the three contributor-month specific monetization methods as indexed by $k$, i.e., $mon_{type}_{i,1,t} = 1$ denotes the contributor adopting VIP subscription and $= 0$, otherwise. The same coding method applies to $mon_{type}_{i,2,t}$ and $mon_{type}_{i,3,t}$ respectively for the monetization methods of virtual gifting and IP subsidy. A panel-level logit specification allows us to control for the unobserved contributor-specific effect. Nevertheless, we also intend to have control variables such as the number of total users in the platform, the number of the contributor’s posts before UGC monetization, the days since the contributor’s registration on the platform, etc.

The Impact of Micro-celebrity Tactics on the Economic Value of UGC Monetization

Two set of independent variables need to be defined. The first set is UGC quality. As the contributors in SIS offer analyses or recommendations about the stock market, UGC quality is defined as how well the content can predict the stock market movements. As stated early on, sentiment of content is used to represent such predictions. The sentiment is said to be positive (negative), if predicting an upward (downward) movement in the stock market (Bollen et al. 2011; Hochreiter 2015). Based on machine learning techniques, we use the Naive Bayesian Classifier to calculate the sentiment ratio of the content (Bollen et al. 2011; Tan et al. 2009) post by one contributor in one day and compare it to both index changes and trading volume in the respective day. If one contributor $i$ successfully predicts the market by $s$ trading days in a period of $n$ trading days, we have $quality_{i}^{n} = s/n$. Thus, based on index changes and trading volume, we have two variables for the UGC quality, $quality_{i,1}^{n}$ and $quality_{i,2}^{n}$.

The second set of variables is the three micro-celebrity tactics, namely visibility, affiliation and endorsement. Utilizing the Linguistic Inquiry and Word Count (LIWC; see (Pennebaker et al. 2015)) software, we use text-mining techniques (Feldman and Sanger 2007) to count the occurrence of the respective tactics. For example, as aforementioned in the Literature Review section, affiliation consists of three practices, “collective referring”, “asking the crowds” and “demanding actions”. As an example, the frequency of the pronoun “we”, the co-occurrence of interrogative clause and pronoun “you”, as well as imperative clauses in all the content of a contributor can be tallied to account for the measure of affiliation.

Noteworthy, endogeneity is common in the studies related to social networks (Handcock et al. 2007; Hartmann et al. 2008; Wasserman and Faust 1994). To address potential endogeneity issues (for example, a contributor’s UGC quality, micro-celebrity tactics and the value of UGC monetization might be influenced by unobserved or latent variables), we explicit account for the latent variable(s) using a data augmentation approach (Tanner and Wong 1987; Wei and Tanner 1990). Naming the latent variable as the “latent ability” (of the contributor), we allow the quality of UGC and each micro-celebrity tactic to be a function of the contributor’s latent ability. So we propose the following model,

$$mc_{i,j} = \gamma_{0,j} + \gamma_{1,j} Ability_{i} + \delta_{i,j}$$

$$quality_{i,j} = \alpha_{0,j} + \alpha_{1,j} Ability_{i} + \xi_{i,j}$$

\[ \text{We define success in an absolute term rather a relative term. US$200 per month seems to be a bottom line of success according to iMaibo managers. Nevertheless, we will check other values in our study later.} \]
value\textsubscript{*} = \beta_0 + \beta_1 \text{Ability}_i + \sum_{j=1}^{3} \beta_{2,j} \delta_{i,j} + \sum_{k=1}^{3} \beta_{3,k} \xi_{i,k} + \sum_{j=1}^{3} \beta_{4,j} \delta_{i,j} + \sum_{j,k} \beta_{5,j,k} \delta_{i,j} \xi_{i,k} \\
 + \sum_{m=1} \beta_m \text{mon}_\text{type}_{i,m} + \beta_7 \text{controls} + \epsilon_i 

(6)

Due to potential endogeneity, variables of micro-celebrity tactics and UGC quality cannot enter into Equation (6). Instead, we use the residuals from Equations (4) and (5) as regressors, which are ability-adjusted, tactic- and quality-related variables. This endogeneity treatment is similar to Hui et al. (2007).

The micro-celebrity practices of one contributor may have continuous impacts on his readers. Thus, we utilize data of every contributor since his registration for the analysis. The unit of analysis is at individual UGC contributor level, denoted by i. j indexes the three micro-celebrity tactics (j = 1,2,3 refer to visibility, affiliation and endorsement respectively). k indexes the two UGC quality variables (k = 1 represents the measure based on index and k = 2 as based on trading volume). The quadratic terms is indexed by l. j’ and k’ index the interaction components of micro-celebrity tactics and UGC quality (j’ = 1,2,3 and k’ = 1). [\delta_{i,j}, \xi_{i,k}] \sim N(0, \Lambda) (\Lambda is unconstrained, and allowing nonzero covariances between the \delta_{i,j} and \xi_{i,k}). \epsilon_i is a random i.i.d error term and \epsilon_i \sim N(\theta^2). Value_i is the measure of the monetization’s economic value, which is the revenue the contributor i has obtained. A Tobit model is used in Equation (7) because the revenue cannot be negative. The \beta's are the parameters of interest. A hierarchical Bayesian procedure is used to estimate the parameters in the above model with Markov chain Monte Carlo (MCMC) simulation.

Finally, we also control for the macro market conditions and the UGC contributor related variables, such as trade volume, market volatility, the percentage of VIP content, the size of followers, the amount of content, the days since registration, the days since monetization, the year since participating in stock market, etc.

**Potential Contributions and Conclusion**

Utilizing a unique dataset from a large Chinese SIS, we empirically investigate the phenomena of UGC monetization. Our study can contribute to the literature in the following ways. First, the economic value of UGC on e-commerce and firms (Chevalier and Mayzlin 2006; Duan et al. 2008; Goh et al. 2013) has been extensively studied, however, to what extent the UGC contributors themselves can harvest economic benefits from UGC lacks empirical examinations. By accentuating the role of micro celebrity practices in profiting from monetization, we underscore that in addition to the content per se, contributors need to interact with readers, since readers may also factor the social activities of contributors into considerations.

Secondly, by juxtaposing the three different UGC monetization methods observed in our data, we unravel the differential effects and relative effectiveness of them on both the platform and individual contributors, thereby complementing and enriching past studies (Ghosh and McAfee 2011; Terada et al. 2013). The existence of potentially varying findings of different methods suggests that researchers should incorporate the nature of the platform and users into the further design of the UGC monetization methods.

Thirdly, our study contributes to the literature of financial information demand by showing that investors (i.e. readers) seek and consume such information from varied sources and of varying quality levels. Further studies can build on our work to examine whether this phenomenon will result in better or worse investment returns for retail investors as well as investigate individual investor behaviors by leveraging the readily available individual-level data in SIS and other FinTechs.

Finally, our study also presents significant managerial implications. For example, even if with monetization methods at hand, when a contributor should start to monetize his produced content remains a vital issue that demands guidelines. To arrive at a better timing, we analyze the social network of the platform and stock market movements to highlight the need of wisely coupling the contributor’s position in the social network with the macro market conditions.
References


