Does Monetary Incentive Lead to Better Stock Recommendations on Social Media?

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Does Monetary Incentive Lead to Better Stock Recommendations on Social Media?

Completed Research Paper

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Abstract

Social media not only is a new channel to obtain financial market information but also becomes the venue for investors to share and exchange investment ideas. We examine the performance consequences of providing monetary incentive to amateur analysts on social media and its implications for crowd-sourced equity research. We find that monetary incentive is effective in increasing the amount of content outputs but does not lead to better stock recommendations. Additional analysis suggests that monetary incentive results in wider stock coverage, a sign of increased content diversity. This study contributes to the understanding of incentive mechanisms for social media communities in the financial context.

Keywords: Monetary incentive, blog, wisdom of crowds, stock market, investment

Introduction

The advance of social media has made it possible for amateurs, who are not employed as professional security analysts and whose credentials are not endorsed by investment banks, to publish their stock opinions and recommendations to the public. Prior studies such as Chen et al. (2014) have shown that stocks opinions shared on social media can be useful in predicting future stock performance. While professional security analysts are incentivized by their high salaries, which are directly tied with their performance (e.g., Stickel 1992), to our knowledge, no prior study has examined whether monetary incentive can be a strong motivation for investors to share value-relevant information on social media and promote crowd-sourced equity research. This study sets out to discover whether monetary incentive, in the form of ad sharing by platform owners, can motivate platform contributors to generate a higher volume of content, and more importantly, improved quality of stock recommendations.

Seeking Alpha (SA), one of the largest online crowd sourced equity research communities for investors, provides a unique setting to quantify the effect of monetary incentive on the quantity and quality of stock analysis and opinion articles. In January 2011, SA launched a premium partnership program that enables its contributors to earn $10 per 1,000 page views received by their “premium” articles, which are published exclusively on SA and not freely available anywhere else on the Internet. After the implementation of this
program, its contributors (both existing and new) can continue to publish non-exclusive articles (we name them as “regular” articles) without monetary compensation on an article-by-article basis.

To answer the question of whether monetary incentive leads to better stock recommendations, we employ the difference-in-differences (DID) approach to compare the articles published by two groups of contributors in the period of two years both before and after the launch of the premium partnership program. We focus our analyses on existing contributors as of January 2011 who remained active and continued to publish articles after the launch of the program. The control group includes 241 contributors who published only regular articles in the study period. The treatment group includes 141 contributors who published only premium articles after the launch of the program. The DID method is able to account for the inherent time-invariant differences between the two groups and estimate the effect of the treatment on the treated group. The financial market context enables us to construct an objective quality measure, prediction accuracy, to assess the information content of articles published on SA by looking at whether the prediction in an article on a particular stock is consistent with its subsequent abnormal stock return (Chen et al. 2014). This is one of the key differences between this study and prior studies on the effects of monetary incentive on online word-of-mouth (WOM) or user-generated content (UGC), which mainly reflects consumers’ personal opinions and lacks an objective content quality measure.

Our analyses show that the number of articles on average increases by 71.7% after a contributor receives monetary payments from the platform. This is equivalent to 15 more articles published by a contributor in two years. However, the quality of the articles written after receiving monetary incentive does not significantly change. In other words, we find no evidence that monetary incentive can lead to either better or worse stock recommendations.

One issue in our context is that contributors voluntarily choose to participate in the program or not, which could potentially result in self-selection bias. To address this problem, we identify an instrumental variable for the participation decision of contributors. The instrumental variable is the average number of comments received by articles published prior to the launch of the program. The main idea is that monetary compensation is directly associated with the page views received by each article and the number of comments on an article is positively correlated with the number of page views. The instrument is not correlated with either the quantity or the quality of a contributor’s articles, because it is an average measure (per article) across all prior articles and both high and low quality articles can attract many comments. The instrument is constructed based on information prior to the launch of the program, so it is more unlikely to directly affect the quantity and quality of the articles published after the launch of the program. With the instrumental variable, our results remain qualitatively the same, although the effect size of monetary incentive on the number of published articles becomes even larger.

To shed more light on this matter, we conduct additional analysis on how monetary incentive changes the behavior of contributors in other content-related aspects. We find that the average article length decreases after monetary incentive is provided. This result suggests the possibility that some contributors may write shorter articles in order to increase the quantity of articles. Furthermore, the number of unique stocks covered by a contributor increases significantly, but the number of industry sectors covered does not seem to have a significant increase when the instrumental variable approach is applied. Taken together, it is possible that contributors expand their scope of coverage by writing on more stocks within the same industry sectors they are familiar with in order to publish more articles to receive monetary payoffs.

To our knowledge, this study is the first one to investigate how offering monetary incentive to amateur analysts on social media affects their content output and quality of stock recommendations. Our result that monetary incentive does not lead to better stock recommendations provides important implications for online communities that facilitates the generation and spread of crowd-sourced investment opinions. Our findings suggest that monetary incentive is effective in promoting community engagement and to certain extent increasing content diversity but it does not necessarily encourage the sharing of value-relevant information by investors on social media sites.

The remainder of this paper is organized as follow. In the next section, we provide a brief review of three research streams closely related with this study. We then introduce our dataset and present the empirical model and analysis. The last section concludes and discusses our limitations.
Literature Review

This study is first closely related to the literature on the role of social media in financial markets. Earlier studies (e.g., Tumarkin and Whitelaw 2001, Antweiler and Frank 2004, Das and Chen 2007) examine how posts on Internet message boards affect stock returns and trading volumes. More recently, Bollen et al. (2011) show that Twitter sentiments can predict the stock market index in the short run. With the increasing popularity of social media, researchers also examine whether social media contents reflect the wisdom of crowds (e.g., Chen et al. 2014, Hill and Ready-Campbell 2011, Nofer and Hinz 2014) in stock market predictions. Chen et al. (2014) use articles and comments posted on Seeking Alpha and show that stock opinions on social media can predict the future performance of individual stocks in the long run. Jame et al. (2016) use crowdsourced earnings forecasts from Estimate and show that earnings forecasts posted by amateur analysts are incrementally useful in forecasting earnings and measuring the market’s expectations. Xie et al. (2017) investigate how network structure plays a role in affecting the prediction accuracy of social media analytics for financial markets. Our study differs from these prior studies in that we focus on how monetary incentive provided by online community owners changes the behavior and performance of amateur analysts on social media.

This study also builds upon the large economics literature that investigates the performance consequences of different monetary incentives. Monetary incentive has been identified by prior studies as one of the most important motivations to promote effort and performance, along with intrinsic motivation and image motivation (e.g., Benabou and Tirole 2003, Tang et al. 2012, Toubia and Stephen 2013, to name a few). Although economic theories suggest that an increase in financial rewards provided by an activity can improve the effort and performance of participants, some studies (e.g., Deci et al. 1999, Gneezy and Rustichini 2000) show that contingent rewards can also be counterproductive, especially in the long run. One possible reason for this is that intrinsic motivations could be crowded out by extrinsic incentives, leading to the participant’s decreased outputs (e.g., Benabou and Tirole 2003, Liu and Feng 2016).

Finally, our study is also related with the growing literature that examines how monetary incentive affects the quantity and quality of customer reviews and product sales. Most empirical studies find that monetary incentive increases the volume of customer reviews (e.g., Burtch et al. 2017, Wang et al. 2016, to name a few), but it either is associated with reduced quality of customer reviews (e.g., Ghasemkhani et al. 2016) or does not affect quality at all (e.g., Wang et al. 2012). Liu and Feng (2016) build a theoretical model to explain the contradictory results observed for the impact of monetary incentive on user-generated content (UGC). Wang et al. (2016) also study the relationship between paid customer reviews and product sales. They find that when a retailer reduces monetary incentives for writing reviews, product sales decrease significantly. The financial context of this study makes it different from all prior studies in the literature of monetary incentive on UGC contribution, because customer reviews mainly reflect a customer’s personal and subjective opinions based on the customer’s experience with a product (i.e., there is no right or wrong), but stock opinions and recommendations will eventually be validated by the market (i.e., the quality of stock recommendations can be accurately assessed). Therefore, the results on the effects of monetary incentive on paid customer reviews may not generalize to the stock market context.

Data

Seeking Alpha is one of the biggest investment-related social media websites in the U.S. It had 7 million average monthly unique visitors in 2016 (Seeking Alpha 2017). The website relies on a crowdsourced contributor network to publish analysis and opinion articles on a broad range of stocks including small- and mid-cap stocks. An editorial panel reviews all submitted articles and may provide feedback to improve clarification but not to interfere with the contributor’s viewpoint. If deemed of adequate quality, these articles are then published on the SA website. In response to these articles, any interested user can write a commentary, sharing his or her own view, which may agree or disagree with the author’s view on the stock in question.

We download all articles and comments posted on SA from 2009 to 2012. Each article is tagged with one or more stock tickers. Single-ticker articles focus solely on one stock, making it relatively easy to extract the author’s opinion on that company. Multiple-ticker articles discuss more than one stock in the same article, rendering extraction of the author’s various opinions for each of the tagged stocks difficult, if not impossible. We therefore focus our analysis on the single-ticker articles, which comprise roughly one-third
of all articles published on SA. The information we collect about each article includes the following items: article ID, title, main text, date of publication, author name, and stock ticker. We also extract all commentaries written in response to the single-ticker articles in our sample. The information we collect about each commentary includes the following items: article ID, comment ID, main text, date the comment is made, and author name. Whether the author of an article receives monetary compensation from SA or not is not public information. SA has provided us with proprietary data on whether an article is premium or regular (i.e., the author of a premium article receives payment from SA). For all the stocks covered in our sample, we collect financial-statement and financial market data from Compustat and the Center for Research in Security Prices (CRSP), respectively.

The sample period is set to be 2009 to 2012, which includes two years of data both before and after the event of introducing the premium partnership program (i.e., January 2011). In order to have both a control group and a treatment group, we restrict the sample to existing contributors as of January 2011 who remained active and continued to publish articles after the launch of the program. The control group includes 241 contributors who published only regular articles in the study period. The treatment group includes 141 contributors who published only premium articles after the launch of the program.

Empirical Analysis

We have two main dependent variables, $\log(\text{ArticleQuantity}_{it})$ and $\text{ArticleQuality}_{it}$, which denote the quantity and quality of content output by contributor $i$ in time period $t$, respectively. $\log(\text{ArticleQuantity}_{it})$ is constructed as the natural log transformation of the number of single-ticker articles published by contributor $i$ in time $t$. $\text{ArticleQuality}_{it}$ is measured as the percentage of single-ticker articles that correctly predict future stock returns. The prediction accuracy of each single-ticker article $j$, $\text{Accuracy}_{ij}$, is calculated as follows. To quantify and study the views reflected in SA articles, we employ textual analysis. Specifically, we build on prior literature, suggesting that the frequency of negative words used in an article captures the tone of the report (e.g., Das and Chen 2007; Tetlock 2007; Tetlock, Saar-Tsechansky, and Macskassy 2008; Li 2008; Loughran and McDonald 2011; Chen et al. 2014). We use the negative word list compiled by Loughran and McDonald (2011) to characterize the views expressed in SA articles. An article is considered “bullish” if its fraction of negative words is below the median of its overall distribution; an article is considered “bearish” if its fraction of negative words is above the median. For each article in our sample, we compute the ensuing cumulative three-month abnormal return. There is a potential concern that SA articles may incite naïve investor reaction. That is, SA articles reflect false or spurious information yet still cause investors to trade in the direction of the underlying articles and move prices accordingly. To alleviate this concern, we skip the first two days after article publication when computing the cumulative abnormal return. $\text{Accuracy}_{ij}$ equals to 1 if a bullish article is followed by positive abnormal returns OR if a bearish article is followed by negative abnormal returns. Otherwise, $\text{Accuracy}_{ij}$ is set to be 0. $\text{ArticleQuality}_{it}$ is the sum of $\text{Accuracy}_{ij}$ for all articles published by contributor $i$ in time $t$ divided by $\text{ArticleQuantity}_{it}$. Note that $\text{ArticleQuality}_{it}$ is expected to be 0.5 if a contributor without any valuable information simply does random guessing when predicting the sign of future abnormal returns.

Descriptive Analysis

To get an initial idea of the behavior of contributors on SA, we plot the average quantity and quality of the articles published by the contributors in the two groups. Figure 1 presents the average number of single-ticker articles per contributor in each month of the study period for both the control group and the treatment group. On average, contributors in the control group publish more articles than contributors in the treatment group in most months. Without monetary incentive, an average contributor in the control group tends to publish fewer articles over time in the entire study period. This is consistent with the general observation that many online contributors become less active or completely inactive after a certain time period. By contrast, an average contributor in the treatment group does not follow this decreasing trend but to some extent publishes more articles after receiving monetary incentive.

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1 As a robustness check, we also construct the article quality measure using the cumulative one-month and six-month abnormal returns. Our results remain largely the same (See Table 5).
Does Monetary Incentive Lead to Better Stock Recommendations

Figure 1. Average Number of Articles per Contributor in each Month

Figure 2. Average Article Quality in each Month
Figure 2 presents the average article quality across contributors in each group over time. The average quality is around half for both groups, although the variation of the treatment group is larger than that of the control group. Overall, Figures 1 and 2 together suggest that monetary incentive increases the content output produced by contributors but does not lead to a clear improvement in predictive accuracy.

**Monetary Incentive and Article Quantity/Quality**

We now conduct the analysis under the regression framework. From Figure 1, we can learn that the behavior of regular contributors is potentially different from that of premium contributors. To explicitly control for the inherent differences between these two groups, we employ the difference-in-differences (DID) approach and specify the following model as described in Equation (1). The idea of the DID method is that the effect of the treatment on the treated group can be captured by the change in the post-event differences in the outcome variables between the control and treatment groups compared with the pre-event differences. Following the suggestion by Bertrand et al. (2004), we implement the standard two-period DID estimator instead of adopting a contributor/month panel (i.e., there are multiple monthly observations in both pre-event and post-event periods) to avoid the downward biased estimation of the standard errors for model coefficients, resulting from serial correlations. In addition, many contributors may not write any article in certain months, so it is reasonable to aggregate the monthly observations over a longer period to avoid zero observations for article quantity and missing values for article quality.

\[ Y_{it} = \text{Treatment}_i \times After_t + After_t + \log(ActivePeriod_{it}) + f_i + \epsilon_{it} \]  

(1)

The dependent variable is either \( \log(\text{ArticleQuantity}_{it}) \) or \( \text{ArticleQuality}_{it} \). \( \text{Treatment}_i \) is 1 for contributors in the treatment group and 0 for contributors in the control group. \( \text{After}_t \) is 0 for \( t=1 \) (before the launch of the premium program) and 1 for \( t=2 \) (after the launch of the premium program). \( \text{Treatment}_i \times \text{After}_t \) is the main variable of interest. \( \text{ActivePeriod}_{it} \) is the number of days contributor \( i \) is active in time period \( t \). Note that our sample of contributors include only existing contributors at the time of launching the premium partnership program. In the period before the event, if a contributor published an article before the study period, then \( \text{ActivePeriod}_{it} \) is the length of the pre-event period. If a contributor started to publish the first article in the middle of the pre-event period, \( \text{ActivePeriod}_{it} \) is the number of days between the publication date of the first article and the end of the pre-event period. In the period after the event, \( \text{ActivePeriod}_{it} \) is the length of the post-event period if the contributor continued to publish articles after the end of the study period. If a contributor stopped to publish articles in the middle of the post-event period, \( \text{ActivePeriod}_{it} \) is the number of days between the beginning of the post-event period and the publication date of the last article by the contributor. \( f_i \) is the individual fixed effects, which absorbs the time-invariant variable \( \text{Treatment} \). \( \epsilon_{it} \) is the error term.

One issue to be addressed is the self-selection problem that could lead to potential endogeneity. Different from a randomized experimental design, premium contributors in our context self-selected to participate in the premium partnership program instead of being randomly assigned to it. Following Sun and Zhu (2013),\(^2\) we employ the instrumental variable approach and identify a valid instrument that is correlated with the decision of participating in the program but does not affect the dependent variables except through the participation decision. The instrument we utilize is the average number of comments received by a contributor’s articles published prior to the event, \( \text{CommentsPerArticle}_i \). To enjoy the benefits of the premium partnership program, a contributor’s articles need to have a significant amount of page views. The number of page views received by each article published before the event is not available, but the number of comments on each article is likely to be positively correlated with the number of page views. However, this variable is not correlated with either the quality or the quantity of a contributor’s articles. It is an average measure across all prior articles but not the total number of comments, so it is unrelated with the number of articles published before. It is also uncorrelated with the quality (or predictive accuracy) of a contributor’s articles, because both high and low quality articles can receive many comments. On one hand, when readers disagree with the view shared in an article, many of them write comments on the article. It is

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\(^2\) Sun and Zhu (2013) examine how participating in an ad-revenue-sharing program of a Chinese portal site motivates bloggers to shift toward popular content. To instrument for a blogger’s decision to join the program, they employ the number of months since a blogger’s first post (i.e., blogging age) and the average number of posts per month for the blogger in the past (i.e., blogging frequency).
possible that such an article cannot accurately predict the future stock return even though it may receive many comments. On the other hand, if an article is truly insightful and accurately predicts the market movement, it can also attract a lot of discussions in comments. It is important to note that the instrument is constructed using information before the event, so it is more unlikely to directly affect the number and quality of the articles published after the event.

<table>
<thead>
<tr>
<th>Variable</th>
<th>#Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Main Dependent and Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArticleQuantity</td>
<td>764</td>
<td>22.13</td>
<td>107.24</td>
<td>1</td>
<td>4</td>
<td>2,145</td>
</tr>
<tr>
<td>ArticleQuality</td>
<td>764</td>
<td>0.51</td>
<td>0.31</td>
<td>0</td>
<td>0.50</td>
<td>1</td>
</tr>
<tr>
<td>ActivePeriod</td>
<td>764</td>
<td>512.29</td>
<td>240.97</td>
<td>1</td>
<td>639.50</td>
<td>711</td>
</tr>
<tr>
<td><strong>Panel B: Instrumental Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CommentsPerArticle</td>
<td>382</td>
<td>8.58</td>
<td>7.68</td>
<td>0</td>
<td>6.50</td>
<td>61.85</td>
</tr>
<tr>
<td><strong>Panel C: Content Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ArticleLength</td>
<td>764</td>
<td>818.38</td>
<td>472.79</td>
<td>43</td>
<td>714.86</td>
<td>6,004</td>
</tr>
<tr>
<td>TickerCoverage</td>
<td>764</td>
<td>10.09</td>
<td>36.57</td>
<td>1</td>
<td>3</td>
<td>648</td>
</tr>
<tr>
<td>SectorCoverage</td>
<td>764</td>
<td>2.64</td>
<td>2.04</td>
<td>1</td>
<td>2</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 1. Summary Statistics

Panel A and Panel B of Table 1 present the summary statistics of the dependent/independent and instrumental variables described above. The number of observations is 764 for dependent and independent variables constructed for both pre- and post-event periods. The mean of ArticleQuantity (without log transformation) is 22.13, which is equivalent to about one article per month for each contributor. The variation in the number of published articles across contributors is large, as the standard deviation is 107.24. The median number of published articles in two years is only 4, but the maximum number reaches 2,145. The mean of ArticleQuantity is 0.51, which is slightly larger than 0.5, the expected average with no valuable information. This is consistent with the results in Chen et al. (2014) and indicates that the opinions revealed on SA on average contain value-relevant information about the long term performance of stocks. The standard deviation is 0.31, suggesting that there is a significant variation in the predictive accuracy of articles written by different contributors. The mean of ActivePeriod is 512.29 days, which is roughly 17 months. The median is 639.50 days (21 months) and larger than the mean, suggesting that most contributors are active almost over the entire study period. However, there are a few contributors that abandoned the site shortly after the launch of the program, as the minimum of ActivePeriod is only 1 day. The number of observations is 382 for the instrumental variable constructed using information in the pre-event period. The mean and median of CommentsPerArticle is 8.58 and 6.50, respectively. The minimum is 0 but the maximum reaches 61.85.

Table 2 presents the estimation results for Equation (1). The dependent variable in Columns (1) and (2) is Log(ArticleQuantity) and the dependent variable in Columns (3) and (4) is ArticleQuality. All columns include the fixed effects in the estimation, and Columns (2) and (4) report the results with instrument variables using two-stage least squares (2SLS).

The coefficient estimate on Treatment × After in Column (1) is 0.717 and statistically significant at the 1% level, suggesting that the number of articles published by a contributor on average increased by 71.7% after monetary payments are provided for writing articles. The result from 2SLS estimation is consistent with the fixed effects estimator, but the coefficient estimate on Treatment × After increases to 1.127 in Column (2), indicating that the number of articles published by a contributor on average increased by 112.7% after being motivated by monetary payments. However, we observe very different results when the dependent variable is the article quality. The coefficient estimates on Treatment × After, are both positive but statistically insignificant at the 10% level in Columns (3) and (4). These results suggest that monetary
incentive is effective in driving up the quantity of content outputs by contributors but it does not lead to the contribution of articles of higher quality.

<table>
<thead>
<tr>
<th></th>
<th>Log(ArticleQuantity)</th>
<th>ArticleQuality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Treatment × After</td>
<td>0.717*** (0.099)</td>
<td>1.127*** (0.472)</td>
</tr>
<tr>
<td>After</td>
<td>-0.498*** (0.060)</td>
<td>-0.647*** (0.179)</td>
</tr>
<tr>
<td>ActivePeriod</td>
<td>0.375*** (0.038)</td>
<td>0.356*** (0.044)</td>
</tr>
</tbody>
</table>

Specification: FE, FE/2SLS
Authors: 382, 382
Observations: 764, 764
Within R²: 0.333, 0.303, 0.001, 0.001

Table 2. Impact of Monetary Incentive on Article Quantity and Quality

The results for control variables in Table 2 are consistent with expectations. The coefficient estimate on After is negative and statistically significant at the 1% level in both Columns (1) and (2). This is consistent with the decreasing pattern revealed in Figure 1, which again indicates that the productivity of a contributor decreases over time. The coefficient estimate on After is negative but statistically insignificant at the 10% level in Column (3) and marginally significant at the 10% level in Column (4). This suggests that the quality of articles written in the post-event period is on average similar as that of articles written in the pre-event period. The coefficient estimate on ActivePeriod is positive and statistically significant at the 1% level in both Columns (1) and (2), because the longer a contributor is affiliated with the SA site, the more articles the contributor writes. However, the length of the membership is uncorrelated with the quality of articles written by a contributor, as the coefficient estimate on ActivePeriod is statistically insignificant at the 10% level in both Columns (3) and (4).

<table>
<thead>
<tr>
<th></th>
<th>Treatment × After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(CommentsPerArticle) × After</td>
<td>0.148*** (0.035)</td>
</tr>
<tr>
<td>After</td>
<td>0.067 (0.074)</td>
</tr>
<tr>
<td>ActivePeriod</td>
<td>0.039** (0.019)</td>
</tr>
</tbody>
</table>

Specification: FE
Authors: 382
Observations: 764
Within R²: 0.408
F-statistics: 86.91

Table 3. First-Stage Regression and Instrument Relevance

We report the first-stage results for the 2SLS estimation in Table 3 to illustrate the relevance of our instrumental variable. Because the main variable of interest is Treatment × After, so we also interact the instrument with the variable After. We find that Log(CommentsPerArticle) × After is positively correlated with Treatment × After.
Monetary Incentive and Article Content

To further investigate how monetary incentive changes the behavior of contributors, we define three other content-related variables and conduct a similar set of analyses as in Table 2 but replace the dependent variable in Equation (1) with the following new variables. ArticleLengthit is the average number of words in articles written by contributor i in time period t. TickerCoverageit is the number of unique stocks covered by articles written by contributor i in time period t. SectorCoverageit is the number of unique industry sectors covered by articles written by contributor i in time period t. Article length measured in number of words can be another measure of a contributor's effort in sharing their investment views and opinions in addition to the simple count of article numbers. It is possible that contributors may write shorter but more articles in response to monetary incentive assuming that it takes the same amount of time and effort to write the same number of words. As to the ticker and sector coverage, a key constraint each contributor faces is that it takes a significant amount of time and effort for any contributor to get familiar with the fundamentals of a public company and gather the relevant information about an industry sector. In light of this, a contributor can potentially adopt two approaches: one is to cover a few tickers/sectors but write as many articles as possible on each target company or industry sector, and the other is to cover more tickers/sectors but write only a few articles on each. Thus, by studying how monetary incentive affects the ticker/sector coverage, we can distinguish between the two approaches adopted by contributors in order to write more articles.

The summary statistics of these three variables are provided in Panel C of Table 1. The average length of SA articles is 818.38 words. The standard deviation is 472.79, implying that there is a sufficient level of variation in the length of different articles. The mean and median number of stocks covered by a contributor in each time period is 10.09 and 3, respectively. The maximum number of stocks covered can reach to 648. The mean and median number of industry sectors covered by a contributor is 2.64 and 2, respectively, while the maximum reaches 9. These statistics suggest that on average a contributor specializes in a few industry sectors and covers a small range of firms.

<table>
<thead>
<tr>
<th></th>
<th>Log(ArticleLength)</th>
<th>Log(TickerCoverage)</th>
<th>Log(SectorCoverage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Treatment</td>
<td>-0.059 (0.046)</td>
<td>-0.534** (0.243)</td>
<td>0.504*** (0.081)</td>
</tr>
<tr>
<td>× After</td>
<td></td>
<td></td>
<td>0.862** (0.389)</td>
</tr>
<tr>
<td></td>
<td>0.090*** (0.028)</td>
<td>0.263*** (0.092)</td>
<td>-0.330*** (0.049)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.461*** (0.147)</td>
</tr>
<tr>
<td>After</td>
<td>0.028 (0.018)</td>
<td>0.051 (0.023)</td>
<td>0.279*** (0.031)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.261*** (0.037)</td>
</tr>
<tr>
<td>ActivePeriod</td>
<td>0.139*** (0.019)</td>
<td>0.134*** (0.022)</td>
<td></td>
</tr>
<tr>
<td>Specification</td>
<td>FE</td>
<td>FE/2SLS</td>
<td>FE/2SLS</td>
</tr>
<tr>
<td>Authors</td>
<td>382</td>
<td>382</td>
<td>382</td>
</tr>
<tr>
<td>Observations</td>
<td>764</td>
<td>764</td>
<td>764</td>
</tr>
<tr>
<td>Within R²</td>
<td>0.036</td>
<td>0.001</td>
<td>0.275</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.238</td>
</tr>
</tbody>
</table>

Table 4. Impact of Monetary Incentive on Article Length and Stock / Sector Coverage

Table 4 reports the results for how monetary incentive affects the length of published articles and the coverage of stocks and industry sectors. Similarly as in Table 2, we also report the results for both FE and FE/2SLS estimators. The results are roughly consistent between these two specifications and the coefficient estimates on Treatment × After are larger in magnitude with the instrumental variable than that of including fixed effects only. Specifically, the length of articles written by contributors does not change significantly after monetary incentive is offered as shown in Column (1), but after applying the instrumental variable approach, we see a significant decrease in the average article length in Column (2). While the result in Table 2 suggests that a contributor publishes more articles with the presence of monetary incentive, the result in Table 4 further implies that contributors could potentially cut down the length of articles in order to write more articles.
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to publishing more articles. In addition, results in Columns (3) and (4) suggest that a contributor covers more stocks after receiving monetary incentive. However, although the coefficient estimates on $Treatment_i \times After$ are both positive in Columns (5) and (6), the coefficient estimate is statistically insignificant at the 10% level in Column (6) after applying the instrumental variable approach. In sum, it is possible that contributors may push themselves to study more firms in order to write and publish more articles, but they may not necessarily try to expand to new industry sectors they are not familiar with.

Although not our main interest, the coefficient estimates on $After$ in Table 4 reveal some interesting patterns about the differences between the post-event and pre-event periods. On average, contributors write longer articles in the post-event period than in the pre-event period (Columns 1 and 2). Contributors also cover fewer tickers and potentially fewer industry sectors in the post-event period than in the pre-event period (Columns 3 to 6). These results can be attributed to certain community-wide changes over time that impact both regular and premium contributors. In addition, the coefficient results on the $ActivePeriod$ variable are consistent with expectations. Article length is not associated with a contributor’s duration of active period, but the longer a contributor stays active, the more tickers and industry sectors she covers.

**Robustness Checks**

We conduct several robustness checks to further validate our results. First, we adopt the total word count of all articles published by each contributor to measure the quantity of content output instead of the article count. This measure considers both article count and average word count per article at the same time. We find that monetary incentive does not significantly increases the total number of words in the instrumental variable estimation (see Columns 1 and 2 of Table 5). Second, we try to use a different time duration when evaluating the future abnormal return and constructing the article quality measure. Our results remain robust (i.e., monetary incentive does not lead to better stock recommendations) when either one month (Columns 3 and 4 of Table 5) or six months (Columns 5 and 6 of Table 5) is selected. Third, we change the study period to include one year (instead of two years) both before and after the launch of the premium partnership program, our results remain largely the same. Results are available upon request.

<table>
<thead>
<tr>
<th>Specification</th>
<th>$Log(TotalWordCount)$</th>
<th>$ArticleQuality-1\text{-month}$</th>
<th>$ArticleQuality-6\text{-month}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Treatment \times After$</td>
<td>0.796*** (0.130)</td>
<td>0.672 (0.605)</td>
<td>0.020 (0.049)</td>
</tr>
<tr>
<td>$After$</td>
<td>-0.500*** (0.028)</td>
<td>-0.454** (0.229)</td>
<td>-0.013 (0.030)</td>
</tr>
<tr>
<td>$ActivePeriod$</td>
<td>0.495*** (0.049)</td>
<td>0.501*** (0.057)</td>
<td>-0.038** (0.019)</td>
</tr>
<tr>
<td>Specification</td>
<td>FE</td>
<td>FE/2SLS</td>
<td>FE</td>
</tr>
<tr>
<td>Authors</td>
<td>382</td>
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<td>382</td>
</tr>
<tr>
<td>Observations</td>
<td>764</td>
<td>764</td>
<td>764</td>
</tr>
<tr>
<td>Within R²</td>
<td>0.300</td>
<td>0.298</td>
<td>0.011</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1.

**Table 5. Robustness Checks**

**Discussion and Conclusion**

Social media is playing an increasingly important role in financial markets. It not only is the new and additional channel to obtain market information besides traditional media outlets (e.g., newspapers and TV) but also becomes the venue for investors to share and exchange investment ideas. This study contributes to the literature on the role of social media in financial markets by providing empirical evidence on how monetary incentive offered by an online investor community affects the quantity and quality of content outputs by contributors. We find that monetary incentive increases content contribution and
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diversity but does not lead to improved quality of stock recommendations. Our results provide important managerial implications for various social media sites. As monetary incentive mechanisms such as ad-revenue-sharing programs are becoming more popular, social media community owners should carefully evaluate the implications of these programs and align them with their goals.

There are a few limitations with our study. First, to infer causality in an observational study, we employ the instrumental variable approach to address the potential selection bias and endogeneity issues. Future research can further validate our results using other methodologies such as randomized experiments. Second, the monetary compensation offered in our context is relatively small, especially compared with the high salary received by professional security analysts. It is possible that the effect of monetary incentive on amateur analysts may depend on the amount of monetary gain.

Acknowledgements

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References


