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An empirical study of the self-fulfilling prophecy effect in Chinese stock market

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Abstract

We analyzed data collected from retail investors in the Chinese stock market from a Fintech mobile platform to find evidence of the self-fulfilling prophecy effect. We found a statistically significant correlation between the predicted and actual Shanghai Stock Exchange Composite Index (SSECI) as well as non-random deviation patterns. We also analyzed participating investor behaviors and discussed the implications and future research.

Keywords: Stock market index; Prediction; Self-fulfilling prophecy effect; Fintech

1. Introduction

Can we predict the stock market movement? Among the dominant normative financial market theory, the efficient market hypothesis (EMH) states that historical stock prices fully reflect all available information. So it is impossible to "beat the market" consistently on a risk-adjusted basis.[1] The rationale of EMH is self-evident. However, still, many methods were being used by investors to capture stock investment opportunity or forecast future stock trend. Among these methods, a majority are the so-called technical analysis, that is using sophisticated statistical analysis techniques to analyze historical stock market data,[2] such as Japanese candlesticks[3] and other charting methods.[4]

In recent years, a study in behavioral finance found that human behavior could significantly influence the financial market movement. For example, the cognitive bias in human behavior, such as hyperbolic discounting[5] combined with financial market complexity,[6] and herding habit by investors[7] are central to the global financial crisis of 2008.[8,9]

Conceiving or changing expectation on future market movement is one of the most common investor behaviors. If market participants' expectation influences a stock market movement and propagates among investors, then the self-fulfilling prophecy effect exists. Several recent studies have confirmed the existence of such influence in social and economic activities.[10−12] For a stock market mainly driven by investor expectation instead of economic fundamental,

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we expect the self-fulfilling prophecy effect would be more significant. Thus, an interesting research question is: *Does the investors' expectation affect the stock market fluctuation?*

In this study, we explored this research question by using data collected from retail investors of the highly speculative The Chinese stock market and found evidence of such correlation. The remaining of this paper consists of three sections, in the literature review section, we introduced crowdsourcing and information market, explained that The Chinese stock market is a highly speculative market that could be influenced by investors' expectations. Next, we explained data collection details and pre-processing measures. In the last section, we presented the data analysis outcome as well as its implication for information market research and financial market practitioners.

2. Literature review

2.1. The wisdom of the crowd

In 1906, British statistician Francis Galton found that though ordinary villagers did not know how much meat a cattle could produce, their aggregated guess could reach almost the exact right weight. Thus, he concluded that even when most participants have little professional knowledge, when there is big enough crowd, their aggregated amateur wisdom is still close to actual result.[13] This is one of the earliest examples of so-called *wisdom of the crowd*.[14]

To fully unleash the power of the crowd and get an accurate outcome, we need a large enough participation and independent estimation from each of them. These are two conditions crucial for the wisdom of the crowd. Such requirements could be costly to set up. However, the Internet and World Wide Web provide a smooth and costless method to reach and assemble a large but diversified online crowd. It also allows us to collect and aggregate their independent prediction in real time. As a result, information economists have experimented on the Web-based information prediction market, which aggregating disperse information contributed by individuals into efficient forecasts of uncertain future events.[15]

They found that such market outperforms most moderately sophisticated benchmarks. Information markets have been applied in almost all social-economic aspects of our daily life. The rule of thumb for organizing such a market is to allow those individual participants who have insights on an issue to be incentivized to reveal their real insights independently.[16]

One successful example of such a market is Iowa Electronic Market or IEM, designed and created by faculty members at the University of Iowa in 1998.[17] This information market used a naturally occurring future market trading mechanism to encourage participants betting on their insights in the US political environment. It successfully predicted the outcome of the US presidential election in the last 18 years.[18]

Another classic example is the Hollywood Stock Exchange or HSX. HSX is a web-based, multiplayer game in which players use the pseudo money to buy and sell "shares" of actors, directors, upcoming films, and film-related options.[19] HSX could be used to predict the box office performance as well as other movie-related competitions. In 2007, HSX Players correctly predicted 32 of the 39 major-category Oscar nominees and seven out of eight top-category winners.

The successful experience of using crowdsourcing method in information market to gain insights and predict future events indicated there is a cost-effective way to polling/crowdsourcing retail investors' expectation or prediction on future stock market movements, i.e., the movement of Shanghai Stock Exchange Composite Index.

2.2. Speculative market

The Chinese stock market is different from the western stock market because of its speculative nature.[20] There are three unique characteristics of the Chinese stock market that led to such characteristics:

Firstly, the Chinese stock market mainly consists of retail investors. There are more than 200 million trading accounts in China, which is about the size of the whole adult population in the United States (http://finance.sina.com.cn/stock/hyyj/20150429/043922068458.shtml). With such a large proportion of retail investors, the Chinese stock market price movement is heavily influenced by the aggregated effect of individual investors' speculation and herding behavior.[21] In contrast, the U.S. stock market mainly consists of institutional investors and their investment behavior is more rationalized and guided by rigorous risk control protocols.

Secondly, the speculation characters of the Chinese stock market is further aggravated by the short term investment tendency of majority investors. Though there is a large number of open trading accounts, the long term owner of Chinese stock is less than 7% of the population.[1] Only recently did the Chinese government begin to consider allowing retirement pension fund into the stock market, which is in sharp contrast to the U.S., where various pension funds held the significant stake in the stock market. Thus, Chinese retail investors trading activity is mostly in the form of short-term speculation, i.e., day trading. Each investment decision is mainly motivated by profiting from short-term stock price change and influenced by herding behavior rather than company fundamentals.

Thirdly, Chinese retail investors believe the central government would serve as the last resort of rescue and ultimate market booster.[22] Specifically, they expect the central government to save the market when there is a market crisis and boost the market when there are significant political events like government or party re-election that needs a harmonious society as support. Indeed, the central government has served such a role since the creation of the first stock exchange in China.[23] Such involvement reinforced the expectation of retail investors and increased speculation behavior.

When these three characteristics working together, the Chinese stock market fluctuation becomes exceptionally susceptible to individual investors' aggregated speculative decision, and one such manifest is self-fulfilling prophecy effect.

2.3. The self-fulfilling prophecy and its effects

The self-fulfilling prophecy effect refers to a prediction that directly or indirectly causes itself to become a reality, by the very terms of the prophecy itself, due to positive feedback between the belief and the behavior.[24]

Self-fulfilling prophecy effect has been observed in the political domain. For example, once people learn about prevailing public opinion via ubiquitous polls or political prediction market (like Iowa electronic market, which has contract price and aggregated polling summaries), such polls or opinions may influence their subsequent voting decision. Consequently, polling results can become self-fulfilling prophecies whereby majorities, whether in support of candidates or policies, grow in a cascading manner due to positive feedback.[12] We could also find the self-fulfilling prophecy effect in the domain of economic decision-making. An experiment conducted by three Netherland researchers found that speculative forecasts of economic change can impact individuals' financial decision behavior, before any realized changes.[10] These findings suggest that forecasted positive or negative change of social or economic activities can influence people's mental model, reduce or stimulate risk-taking, and lead to the intended outcome.

There is one crucial difference between the information market prediction and self-fulfilling prophecy effect though. The assumption of information market prediction is the object of prediction is either independently existing, such as the weight of a cattle, or mainly determined by factors other than prediction itself, such as Presidential election or Oscar nominee. While the assumption of the self-fulfilling prophecy effect is a highly speculative environment that the prediction itself dominate the actual outcome while other factors contribute or influence little, which we believe is the case of Chinese stock market.

As explained in the previous section, the Chinese stock market is highly speculative due to its unique characters. In such a market, retail investors' prediction of the market movement is influenced by news, expectations of government initiatives, or even rumors via word-of-mouth, instead of the company and economic fundamentals. With such type of self-fulfilling mechanism, when a majority of investors believe a non-substantial government announcement would drive the market up or down and then making invest decisions, it could propagate and trigger a positive feedback loop of self-fulfilling, further driving up or beating down the market, sometimes even leading to stock market bubble or crisis when other conditions met and push the trend to extreme.[21] Thus, we argue the Chinese stock market is impacted by the self-fulfilling prophecy effect.

It is reasonable to suspect that we could find evidence of the self-fulfilling prophecy effect by analyzing the correlation between predictions made by retail investors and actual market movement. We can also expect the larger the polling base, the higher the correlation we would identify. Since the influence of speculative forces may not be consistent across a single stock, we used macro-level market movement variables, such as the Shanghai Stock Exchange Composite Index (SSECI), as polling target. The comprehensive coverage of SSECI could manifest overall market speculation direction because it has been observed and used by all retail investors. Thus, in our study, we used the crowd-sourcing prediction of SSECI to find evidence of the self-fulfilling prophecy effect.

3. Data collection and cleaning

Based on prior discussion and our research question, we propose that *there is a statistically significant correlation between retail investor prediction and the actual Chinese stock market movement index like SSECI*.

To verify our hypothesis, we collaborated with a Beijing-based Fintech company (referred to as Company A). This company is specializing in innovative stock market investment tools. It operated and maintained a mobile app as well as the WeChat platform for its products and services. The collaboration allows us to tap into this company's user base, which mostly consists of Chinese stock market investors.

The platform allows participants to predict the movement of the SSECI index up to the next six months through its WeChat Public Account. WeChat Public Account is an HTML5 mobile webpage accessible via WeChat APP on a mobile phone. Because most Chinese have a WeChat account on their mobile phone, companies could collect data via interactive features of this account just like using an APP. This avoids the hassle of downloading additional APP so many start-up companies in China prefer it.

Investors could enter their predicted index as well as the expected realization date via their mobile phone. After sending in their prediction, as a reward, they would be able to view the most-recent aggregated forecast for the next seven days, which was continuously calculated and generated by the backend server. Fig. 1 is the WeChat interface we used to collect the data as well as the aggregated prediction chart to participants.

The data collection process lasted from January 2016 through July 2016. After the data collection, we obtained a data set with a total of 214,451 data points contributed by 24,938 different retail investors. The date of contribution ranges from January 5, 2016, to July 20, 2016.

We processed the data set with standard data cleaning procedures. It included the elimination of prediction on a single stock and out of range data due to random or error input. Because the stock index rarely rises or drops more than 3% within a day, we regard any prediction that exceeds such limit as abnormal and eliminated them. Moreover, if the leading time of prediction exceeds one month, the observation is also deleted, because more than 98% leading times

Fig. 1. (right): WeChat data collection interface (left) and results are shown to participants (right).

are less than 30 days. Company A also provides forecasting service on a single stock. The data set we received contained such prediction, and they were also removed.

Finally, we removed data with invalid dates, i.e., those before 2016 due to database or input error, those prediction dates before or on the dates when the prediction is made, and those prediction dates fall on non-trading dates. Table 1 is a summary of the data cleaning outcome.

After the data cleaning, we retained a total of 100,446 valid data observations contributed by 13,659 different retail investors. We used a scatter plot to illustrate its distribution (Fig. 2). Different color in the figure indicated a varying degree of data density on dates.

4. Data analysis

We compose the daily predicted index in two ways. One is the average predicted index, which takes the mean value of all the forecasting values of the day. The other is the median predicted index which takes the median of all the forecasting values of the day. Since we limit the observations within one-month leading time, the predicted index is, in fact, the composite forecasting value given by the investors who have made a prediction within one month. In subsection 4.2, it could be seen that the average leading time is 16.81 days. So the predicted indexes are roughly two weeks before the actual date.

4.1. Predicted vs. actual index

We first compared the average predicted index with the actual index and found the former significantly correlated with the latter (Pearson Correlation: 0.8698, *p-value* <2.2e-16), which validated our self-fulfilling prophecy effect hypothesis (Fig. 3). The high correlation shows that the average predicted index and the actual index has a quite good co-movement, indicating the two indexes influence each other. (The median predicted index has similar but slightly weaker results as the average predicted index. We omitted the detailed results.)

We also found that the average deviation of the average predicted index to the actual index is 31.706 and not randomly distributed (*p-value* = 9.671e-07). The correlation between the deviation and the actual index is −0.3,486,918. This non-random deviation consists of a pattern: *the magnitude of actual index fluctuation always exceeds that of the corresponding predicted index*. For example, when the actual index was in a downturn for a period and change its direction to upward, the magnitude of risen-up would exceed the predicted risen-up, vice versa.

This pattern further confirmed our hypothesis. The stronger the speculation, the more intense of positive feedback loop under self-fulfilling prophecy effect. When most investors believe there is a change in the stock market direction, we could expect the aggregated result would exceed the early expectation with an increasing number of investors taking action to reinforce the belief.

A time series X is said to Granger-cause Y if the lagged values of X provide statistically significant information about future values of Y. Linear and nonlinear Granger causality tests are often used to examine the dynamic relationship between the stock index and return changes.[25] To further analyze the correlation between the predicted and the actual SSECI index, we used linear Granger causality test to examine the relation between the average predicted index, the median predicted index, and the actual index (Table 2), by building VAR models between the predicted indexes and the actual index. We found the significant mutual causal relationship

Table 1
Invalid data distribution.

Invalid Data Type	
Predictions on a single stock	40,037
Single day fluctuation exceeds 3%	65,781
Predictions before the trading day	227
Out of date range prediction	7928
Total	113,973

Note: There is no overlap in the above categories because we removed each category in order.

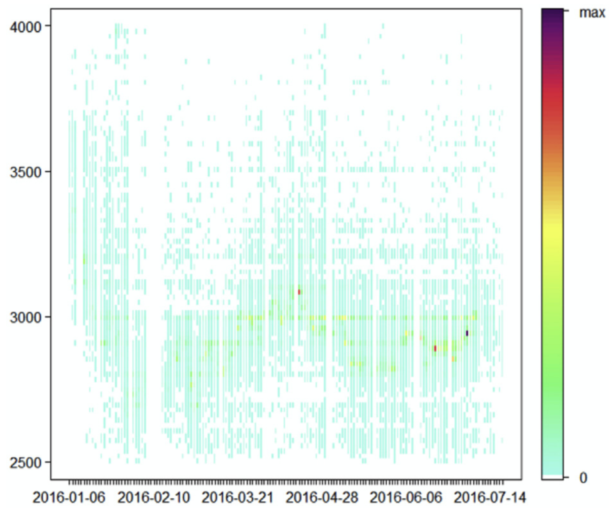

Fig. 2. Scatter plot of the cleaned dataset, color indicates data density.

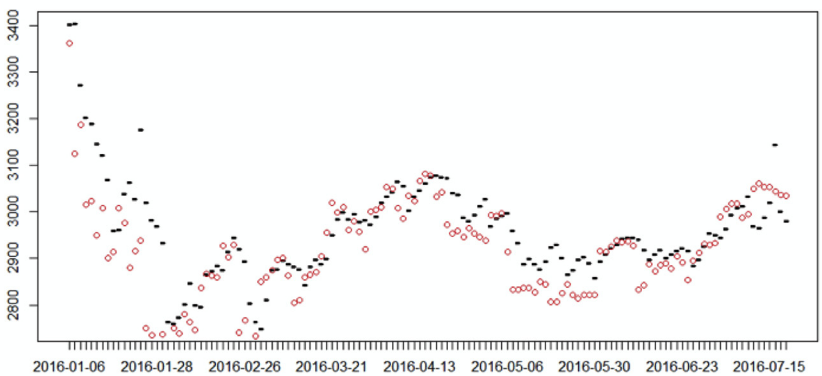

Fig. 3. The average predicted index (in black) vs. the actual index (in red).

between the average predicted index and the actual index. That is, the average predicted index could reflect the market changes around the predicted dates, and the actual market movement can influence the investors' prediction. Though multiple factors influence the actual index, this indicated self-fulling prophecy induced retail investor prediction is at least one contributing factor to the fluctuation of the actual index. Once again, this supported our self-fulfilling prophecy effect hypothesis (see Table 3).

Table 2
Granger causality test result.

Orders	First-order lag		Second-order lag	
	A、C	B、C	A、C	B、C
p-value ①	0.01348*	0.3725	0.0007843*	0.02182*
p-value ②	5.996e-09*	2.2e-16*	9.853e-09*	2.2e-16*
Conclusion	Mutual	C cause B	Mutual	Mutual

Note: A: average predicted index, B: median predicted index, C: actual index, ① indicate left to right causal relation ② indicate right to left causal relation and "*" indicate statistically significant.

Table 3
Distribution of prediction accuracy.

Groups	Participants	Weight	Avg. dev.	Correlation
Dev. <15	2965	21.70%	7.405,016	0.9953
Dev. >15	10,694	78.30%	36.42,826	0.8747
Total	13,659	100%	31.71,935	0.8697

4.2. *User behavior and prophecy fulfilling*

Understanding investor participating behavior would give us more insights into the self-fulfilling prophecy effect in the Chinese stock market. For example, how long it takes for a self-fulfilling prophecy effect to manifest itself from surmise to actual stock market impact? We expect this depends on multiple variables of the market environment, such as media quality, regulation strength, and the credibility of the source of prophecy. For the Chinese stock market, we expect user behavior analysis would reveal its unique cycle for such a prophecy to take effect.

The first variable that could influence the spreading of the stock index prophecy is retail investors' participation. In our data, we found that 76% of participating investors contribute 5 or fewer times of their prediction, 86% contribute 10 or fewer times, and 90% contribute 15 or fewer times. This indicated that most prediction data we collected is like from the randomly selected investor. They are mostly independent of each other. Though persistent participation by investors could help us build the track record of the individual, random participation by a different group of investors allow us to estimate the stock index prophecy effect with less bias caused by the same group. Fig. 4 is the frequency of individual investor participation during the data collection period.

The second variable that could affect the self-fulfilling of index prophecy is the interaction pattern of communication among investors. The most common communication channel among retail investors is popular social media apps, such as QQ, WeChat, and BBS embedded among investment related websites. So it is interesting to know when and how often retail investors would exchange their information and then making investment decisions, which would ultimately determine the realization of any index prophecy.

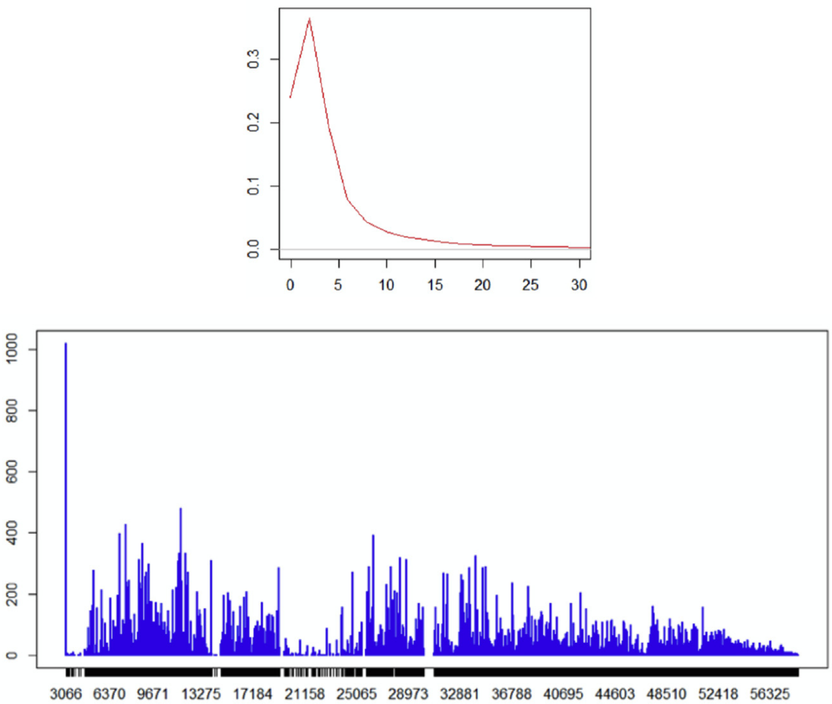

Fig. 4. User participation frequency (top) and distribution of user ID (bottom).

The Chinese stock market opens at 9:30 am and closes at 3 pm. Our dataset indicated that most participants contribute their index prediction between 7 am and 3 pm (see Fig. 5). Fig. 6 shows that the intraday predicting time of the investors. Retail investors prefer to make their prediction within 2 h of morning market opening, stop making predictions during morning trading hour, resume prediction and reach climax at 12 pm, during the lunchtime, then continue making predictions until the close time at 3 pm. So most likely retail investors would exchange their information between 9 am and 12 pm each trading day. In other words, any credible self-fulfilling index prophecy would be spread from mouth to mouth during these three hours and then take their effect in the afternoon and next morning investment decisions. Such an effect would accumulate with each round of spreading until it becomes a reality.

A related variable to retail investor prediction behavior is how many days forward retail investors prefer to? Based on our dataset, participants on average made their predictions ahead of 16.81 days, that is around half a month. We found most predictions forecast fall within the range of 13−27 days in advance though some could be as forward as 3−6 months. This finding indicated there is an average 15−20 days prophecy surmise to market impact cycle believed by most retail investors, which is about consistent with our previous analysis on fluctuation pattern and consistency between predicted and actual exchange index.

Finally, we want to know: do all prophecies equal? We found that the distribution of retail investors in our dataset regarding their predictive power follows 20−80 laws. That is the top 20% of participants predicted index have about 99.53% correlation with actual index. In contrast, the bottom 80% correlates only about 87.47%. This indicated for all those index prophecies, and the top 20% will most likely to be realized while the bottom 80% may eventually disappear during the spreading process.

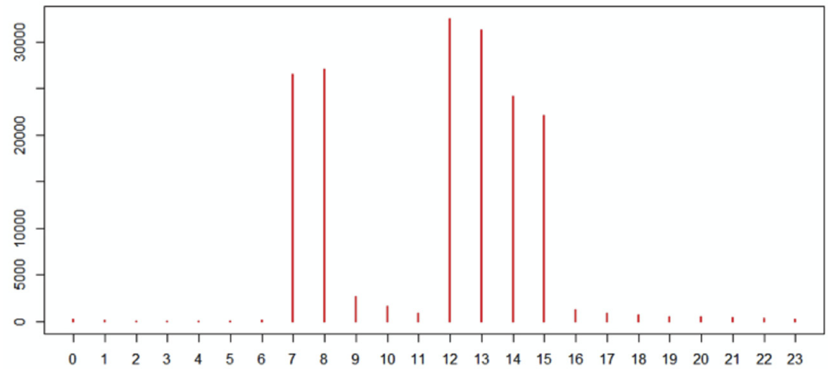

Fig. 5. Distribution of prediction time.

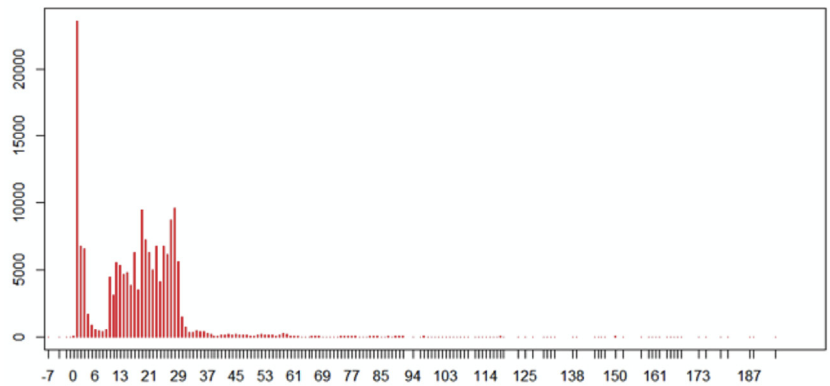

Fig. 6. Distribution of lead time.

5. Implications

This very preliminary study shed new light on using the self-fulfilling prophecy effect to forecast and monitor the stock market trend in a speculative stock market scenario. Recent progress in behavior finance already found the importance of understanding investor behavior in identifying market dynamics. This study specifically indicated that the self-fulfilling prophecy effect could be utilized in a highly speculative market, which could help capture an important market turning signal.

Industry practitioners could consider creating a crowdsourcing stock index futures market, as the Iowa electronic market or HSX. Such a market could encourage investors to put down a small amount of money as their bet on their prediction. As an incentive, investors would receive the monetary reward if their prediction is within the range of accuracy. Such an information market would generate a future stock market movement index, complementary to the index like SSECI. Such a future market allows us to eliminate all non-committal data contributors and dramatically increase data quality. The S&P Volatility Index in the United States is an excellent example in such a direction.

6. Conclusion

In this study, we analyzed a data set about predictions on the future movement of the Shanghai Stock Exchange Composite Index by Chinese retail investors via a mobile platform maintained by a Chinese financial service company. We tested and validated the self-fulfilling prophecy effect by identifying the correlation between retail investor predicted index and actual SSECI index movement. Our study demonstrated the possibility of using retail investor crowdsourcing method to generate a more sophisticated prediction market. We also analyzed investors' behavior. Such behavior would help us better understand their decision-making process.

Conflict of interest

All authors have none to declare.

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