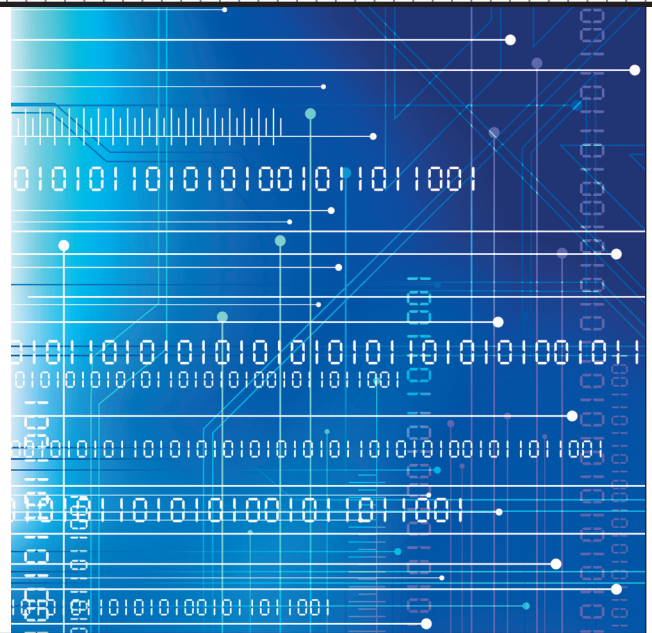


Twitter Mood as a Stock Market Predictor

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Behavioral finance researchers can apply computational methods to large-scale social media data to better understand and predict markets.

It has often been said that stock markets are driven by “fear and greed”—that is, by psychological as well as financial factors. The tremendous volatility of stock markets across the globe in recent years underscores the need to better understand the role that emotions play in shaping stock prices and other economic indices.

A stock market is a large-scale, complex information processing system that responds to a wide variety of socioeconomic factors. As such, its behavior is difficult to model and, consequently, to predict. The *efficient market hypothesis* (EMH) asserts that financial markets are “informationally efficient.” In other words, market prices tend to fully reflect all available information because investors rationally take this into account and act accordingly. This implies, among other things, that it’s impossible to achieve better-than-average market returns over long terms.

Behavioral finance has challenged this notion, asserting that investors don’t always act on the basis

of rational considerations and that their behavior is subject to particular psychological biases and emotions. Consequently, predicting market behavior requires understanding the factors that shape investors’ individual as well as collective behavior.

PREDICTING MARKET BEHAVIOR

Behavioral finance and investor sentiment theory have firmly established that investors’ behavior can be shaped by whether they feel optimistic (bullish) or pessimistic (bearish) about future market values. Theories of social mood and their role in market behavior, such as those proposed as early as the 1970s by Robert Prechter (“What’s Going On?,” *The Elliott Wave Theorist*, 3 Aug. 1979), are also enjoying increasing acceptance.

The recent financial crisis has reinforced the notion that investor sentiment shapes financial markets more than the EMH would allow. Consequently, the question is no longer whether social mood and investor

sentiment affect stock prices, as it was a few decades ago, but rather how we can best measure and model their effects.

Historically, surveys have been the most direct way to measure social mood and investor sentiment. For example, the Conference Board’s Consumer Confidence Index, the University of Michigan’s Consumer Sentiment Index, and Gallup’s Economic Confidence Index measure public sentiment about current and future economic trends. In addition, numerous investment services and organizations including Merrill Lynch, Investors Intelligence, and the American Association of Individual Investors conduct and publish investor sentiment polls.

Such surveys, however, have serious inherent disadvantages. Conducting them is expensive, thus limiting both the number of individuals they can cover and how often they can be repeated in a given time interval. Furthermore, explicit expressions of mood or sentiment could be less reliable than behavior-based indicators.

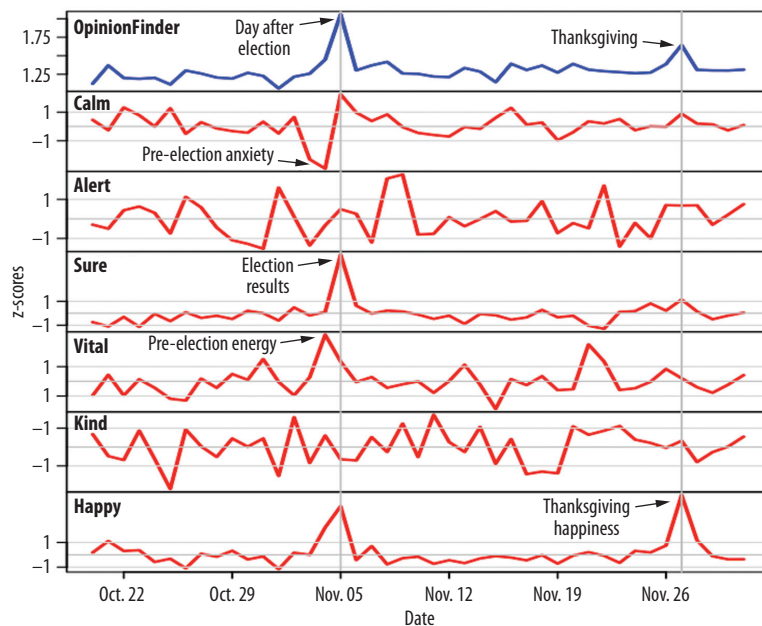


Figure 1. Fluctuation of public mood states from October to December 2008 as measured from large-scale Twitter data by GPOMS and OpinionFinder. Key events—the US presidential election and Thanksgiving—had an effect on public mood that the time series easily picked up.

The rise of social networking environments has opened a new frontier in the development of reliable, scalable, and rapid assessments of the public mood. Recent research efforts led by Alan Mislove (“Pulse of the Nation: U.S. Mood throughout the Day, as Inferred from Twitter,” www.ccs.neu.edu/home/amislove/twittermood) and Peter Dodds (“Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitters,” <http://arxiv.org/abs/1101.5120>) have shown that analysis of geolocated and time-stamped tweets can lead to geographical models of changes in the public mood over time.

In our work, (J. Bollen, H. Mao, and X.-J. Zeng, “Twitter Mood Predicts the Stock Market,” *J. Computational Science*, Mar. 2011, pp. 1-8), we have leveraged sophisticated sentiment-tracking tools and large-scale Twitter data to assess global public mood states at short time intervals. We then used the resulting Twitter mood data to predict stock market values, in

particular the daily fluctuations of the Dow Jones Industrial Average (DJIA), with surprising results.

DATA COLLECTION AND VALIDATION

Our initial analysis in 2010 focused on the year 2008, which was marked by a US presidential election as well as the near-collapse of the world’s financial system, with a corresponding crash of global stock markets.

We obtained a collection of 9,853,498 public tweets posted by approximately 2.7 million users from 28 February to 19 December 2008. Each tweet record contained an anonymous identifier, the submission’s date-time stamp, the mechanism for submitting the tweet (mobile phone, Web, and so on), and the tweet’s content. As most Twitter users know, tweets are limited to only 140 characters—hence the term microblogging. After removing stop words and punctuation, we grouped all tweets submitted on the same date to generate daily time series. We made no

efforts to limit tweets to a particular geographical location or time zone.

We applied two emotion analysis tools to our daily collections of tweets:

- GPOMS, a now proprietary tool that measures six different dimensions of mood often ignored by traditional sentiment-tracking methods—calm, alert, sure, vital, kind, and happy; and
- OpinionFinder (OF; www.cs.pitt.edu/mpqa/opinionfinderrelease), a widely used sentiment-analysis tool that classifies texts in terms of their positive versus negative sentiment and is useful for cross-validation.

For each of the six GPOMS dimensions and OF analysis, we generated a daily time series of public mood fluctuations.

To qualitatively assess the time series’ face validity, we examined mood fluctuations in the two-month period from 5 October 2008 to 5 December 2008, during which the presidential election (4 November) and Thanksgiving (27 November) occurred. Our assumption was that these events had a variegated effect on the public mood that the series should easily pick up.

As Figure 1 shows, the GPOMS time-series data revealed increased nervousness before the election, high energy the day of the election, and public elation as well as assurance the day after the election. The OF results confirm a high degree of positive sentiment the day after the election, but due to its binary nature, the data doesn’t capture any other public mood changes. All seven time series indicate a coherent response to Thanksgiving: happy or positive, but not much more.

A statistical analysis further showed that the OF time series is significantly correlated with several GPOMS time series—namely, sure, vital, and happy—but not with calm, alert, and kind. Because the latter

dimensions might nevertheless play an important role in shaping public mood, we retained them in subsequent analyses.

DATA ANALYSIS

To determine whether public sentiment relates to stock market values, we first applied a Granger causality analysis to our seven public mood daily time series as well as a daily time series of DJIA closing values in the same period.

We then deployed a self-organizing fuzzy neural network (SOFNN) model to test the hypothesis that including public mood measurements can improve the accuracy of DJIA prediction models—in other words, we used the SOFNN model as a diagnostic tool to determine whether our public mood daily time series contained predictive information with respect to DJIA closing values. We chose 28 February to 28 November as the training period and 1 to 19 December 2008 as the test period.

Figure 2 illustrates the methodology and timeline of our approach.

As Figure 3 shows, public mood and DJIA daily time series frequently overlapped in the same direction. Calm had the highest Granger causality relation with the DJIA for time lags ranging from two to six days (p -values < 0.05). Changes in calm values on day ($t - 3$) predicted a similar rise or fall in DJIA values (t), indicating the predictive power of calm with regard to DJIA. Compared with the baseline model of historical DJIA values, adding calm reduced the mean absolute percentage error (MAPE) by 6.15 percent (1.94 to 1.83 percent) and improved direction accuracy by 18.3 percent (73.3 to 86.7 percent). The other four GPOMS mood dimensions and OpinionFinder didn't have a significant correlation with stock market changes.

In sum, public mood as measured along GPOMS dimensions, especially calm, matched shifts in DJIA values that occurred three to four days

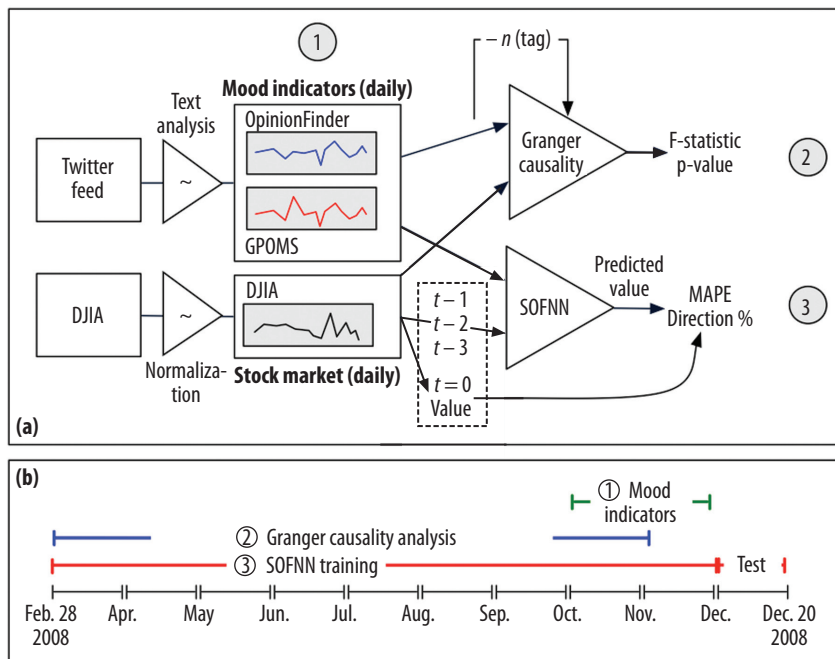


Figure 2. Assessing the correlation between public mood daily time series data extracted from Twitter and Dow Jones Industrial Average (DJIA) closing values: (a) methodology and (b) timeline.

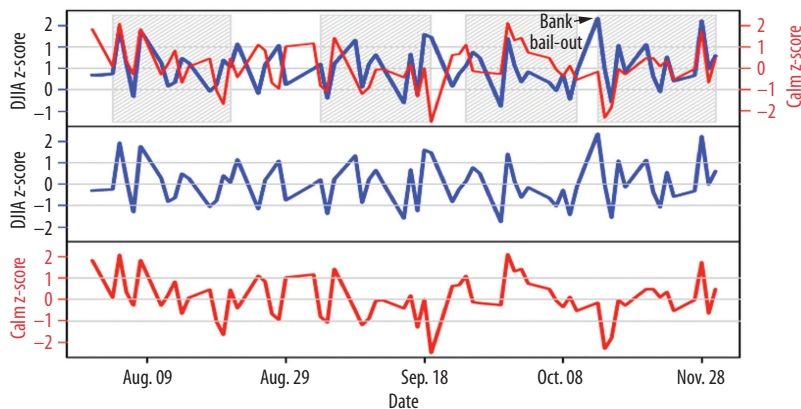


Figure 3. Daily time series of public mood overlaid with those of DJIA closing values. The latter are shifted back three days to highlight where public mood changes predict the DJIA values.

later. This result is consistent with a basic assumption of behavioral finance—emotions play a key role in financial markets.

Behavioral finance as a research field is still in its infancy, but it will increasingly become part of mainstream

finance. Exploiting emerging technologies, researchers can apply computational methods to social-media data to model behavior in financial markets more accurately and on a scale well beyond the limits of traditional controlled experiments.

Our analysis suggests some interesting directions for future research.

First, we only studied the relationship between Twitter mood and the US stock market. Twitter offers a potentially rich source to track public sentiment in other countries—including the UK, Portugal, Japan, and Spain (English, Portuguese, Japanese, and Spanish are the most popular languages on Twitter)—to investigate the impact of mood on their stock markets.

Second, while our results strongly indicate a predictive correlation between Twitter mood and DJIA values, they offer no information on the causative mechanisms. This

remains a crucial area for future research.

Third, researchers might need to take into account social and cognitive effects in which individual agents are endowed with the ability to learn from past experiences and can adjust their trading behavior accordingly.

Finally, there must be more study of financial markets at the aggregate level.

Explaining which stocks are likely to be most affected by sentiment is also an interesting research question. **□**

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