Practical Applications of

Momentum, Mean-Reversion, and Social Media: *Evidence from StockTwits and Twitter*

Practical Applications
Institutional Portfolio Research

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Overview

In **Momentum, Mean-Reversion, and Social Media: *Evidence from StockTwits and Twitter***, from the Summer 2018 issue of ***The Journal of Portfolio Management***, **Shreyash Agrawal, Pablo D. Azar**, **Andrew W. Lo**, and **Taranjit Singh** (all at MIT) demonstrate that social-media activity can significantly affect liquidity on an intraday basis and that negative sentiment has a much larger effect than positive sentiment on liquidity. They propose an intraday trading strategy based on sentiment as reflected by social media and show that the strategy outperforms a basic intraday mean-reversion strategy (before transaction costs).

In their analysis, the authors measure liquidity along several dimensions, including number of trades, number of quotes, number of trades outside the quoted bid–ask spread, turnover, and average spreads. They consider both social media and traditional news as indicators of sentiment.

Practical Applications

- **Negative social-media sentiment has a much larger effect than positive social-media sentiment.** Negative sentiment has twice the effect of positive sentiment.
- **News and social-media data can be used to predict liquidity measures before the market opens.**
- **Social-media sentiment can be used to detect the peak of an intraday boom or the trough of an intraday panic.**

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Key Definitions

Market sentiment

Market sentiment refers to the crowd psychology or overall attitude of investors toward a security or the market as a whole. It is usually measured by market-based indicators, such as price movements or volatility. Here, the authors measure sentiment based on data about news items and social-media activity to measure "news sentiment" and "social-media sentiment" specifically.

Mean-reverting trading strategy

A mean-reverting trading strategy is one that trades against a trend in which price or returns have diverged significantly from prior mean levels. Such a strategy is based on the notion that prices or returns will tend to revert to their prior mean levels.

Momentum

The term *momentum* refers to the notion that rising prices will tend to keep rising and that falling prices will tend to keep falling. More broadly, it refers to the idea that that existing trends are more likely to continue than to stop or reverse. Momentum and mean reversion can be viewed as opposites.

Discussion

In broad terms, the authors assess whether (and to what degree) social-media sentiment and news sentiment lend insight on market activity that is not already captured in other data. Their statistical results show that social-media sentiment displays a correlation with liquidity measures that is not explained by other factors. Additionally, their results show that high levels of social-media messages tend to be followed by increased liquidity and mean-reversion. Their data source for social-media sentiment is minute-level data from PsychSignal, comprising separate scores for positive and negative sentiment. For news sentiment, the authors' data source is the Composite Sentiment Score from RavenPack.

> "As prices shift, market makers who rely on mean-reversion will pull out of the market, triggering a self-reinforcing feedback loop in which prices move even more sharply because of declining liquidity, causing more investors to liquidate their holdings in a panic because of increasing price volatility."
>
> ***—Momentum, Mean-Reversion, and Social Media: Evidence from StockTwits and Twitter***

REGRESSION ANALYSIS

The authors perform regressions using various liquidity indicators as the dependent variables. Their independent variables are (i) news sentiment as measured by the RavenPack Composite Sentiment Score, (ii) positive social-media score from PsychSignal, (iii) negative social-media score from PsychSignal, and (iv) number of social-media messages. The key finding of the regression analysis is that there is greater excess demand for liquidity when social-media sentiment is negative than when it is positive. Additionally, the authors find that both news and social-media sentiment before the market opens are predictive of liquidity after the market opens.

EVENT STUDY ANALYSIS

In addition to the regression analysis, the authors performed event studies in which they match trading activity on 500

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high-capitalization stocks to intraday movements in each stock's social-media sentiment score. They focused on events that produced a social-media sentiment score three or more standard deviations away from a stock's mean social-media score. They considered social-media message activity during a 20-minute interval centered on each event.

The key finding from the event studies is that exceptional social-media scores are preceded by strong momentum and followed by increased liquidity and mean-reverting returns and spreads.

> “The strategy that doubles down on stocks with high message volume consistently outperforms the benchmark mean-reversion strategy.”
>
> ***—Momentum, Mean-Reversion, and Social Media: Evidence from StockTwits and Twitter***

TRADING STRATEGY ANALYSIS

The authors compared an intraday mean-reversion strategy with one augmented by signals from social-media activity. The benchmark strategy calls for trading every 30 minutes based on a stock's returns during the preceding 30-minute interval. It sells all the stocks that posted returns in the top decile and buys all the stocks that posted returns in the bottom decile. All traded stocks have equal weights (positive or negative). The augmented strategy adjusts the weights so that stocks with high social-media activity receive twice the weight of others. The authors define high social-media activity based on two criteria: (i) having more than five social-media messages in the preceding 30-minute interval *and* (ii) having the number of social-media messages in the preceding 30-minute interval exceed the exponentially weighed moving average. Both the benchmark mean-reversion strategy and the one augmented by social-media signals apply 2:1 leverage.

The authors find that, before transaction costs, the social-media augmented strategy consistently outperforms the benchmark mean-reversion strategy. However, both strategies call for extremely active trading. Except for market makers with zero or near-zero transaction costs, transaction costs would likely negate the benefits of either strategy.

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