Intraday online investor sentiment and return patterns in the U.S. stock market

https://www.sciencedirect.com/science/article/pii/S0378426617301589

Highlights

- We analyze an extensive dataset of messages published on the social media platform StockTwits.
- We construct replicable and transparent intraday investor sentiment indicators.
- We report that our field-specific lexicons significantly outperform standard dictionary-based approaches.
- We find that the first half-hour change in investor sentiment helps forecast the last half-hour market return.
- Analyzing users' self-reported strategies, we provide evidence of sentiment-driven noise trading at the intraday level.

We find evidence that when investor sentiment is computed using L_1, L_2 or M_1, the first half-hour change in investor sentiment predicts the last half-hour stock market return.

Even after controlling for lagged market returns, the first half-hour change in investor sentiment remains the only significant predictor of the last half-hour market return.

This finding provides evidence that the intraday sentiment effect is distinct from the intraday momentum effect. Interestingly, we also demonstrate that the intraday momentum effect documented by GHLZ do not hold during the most recent period.

However, on days with no news, investor sentiment affects stock prices

We find that the average annualized return of a strategy using half-hour change in novice investor sentiment as a trading signal is equal to 4.55%, with a Sharpe ratio of 1.496.

- Usually, any **Sharpe ratio** greater than 1.0 is considered acceptable to **good** by investors. A **ratio** higher than 2.0 is rated as very **good**. A **ratio** of 3.0 or higher is considered **excellent**. A **ratio** under 1.0 is considered sub-optimal.

First, we find that when investors are more optimistic during the first 30 min on day *t* than during the last 30 min of day *t*
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1, the S&P 500 index ETF significantly increase during the last half-hour of the trading day. However, all other variations in investor sentiment ($\Delta s_{i,t}$ for i={2,... 12}) are not significant in predictive regressions. This finding illustrates the "timing effect" as investors seem to prefer to wait until "the dust is about to settle" before buying or selling the S&P 500 index ETF based on their initial sentiment. This finding is also consistent with the explanation based on the presence of late-informed investors provided by GHLZ.

Stock Prediction using Deep Learning and Sentiment Analysis

https://ieeexplore.ieee.org/document/9006342

- This paper studies the application of attention-based LSTM deep neural network in future stock market movement prediction.
- We also build stock aggregate dataset and individual dataset including stock history data, financial tweets sentiment and technical indicators in the US stock market.
- The experiment studies the time sensitivity of finance tweet sentiment and methods of collective sentiment calculation.
- We find the finance tweets that are posted from market closure to market open in the next day has more predictive power on next day stock movement.

Table VI Result for Aggregate Dataset

Test Case	Accuracy	MCC
After hours Max Followers	52.27%	0.04092

Table VII Attention-Based LSTM Comparison

Model	Accuracy	MCC
LSTM	52.27%	0.04092
attention-based LSTM	**54.58%**	**0.04780**

Stock price prediction methods generally fall under two categories: Fundamental analysis (FA) and technical analysis (TA). FA is focused on the intrinsic value of a stock by looking at the economic factors, such as revenues, debt, growth rate etc.. FA takes a broader view of a company and considers long term perspective. They believe the return takes time to realize its intrinsic value.

Technical Analysis, on the other hand, concentrates on stock price and tools that were derived from stock price. Due to the sensitivity over the history data, TA is usually considered as an approach for short-term to mid-term investment.