Interaction between Microblog Sentiment and Stock Return: An Empirical Examination

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Outline

1.Introduction

2.Research design

3.Empirical result

4.Conclusion

1.Introduction

➢Backgrounds

1. Social media messages, as a major type of big data, are believed to be the largest data source for public opinion.

2. Opinions reflected in microblogs have provided businesses with great opportunities to acquire insights into their operating environments in real time.

3. In recent years, one particular type of information extracted from microblogs, *sentiment*, referring to the emotional state of users, has been studied for stock market predictive power.

1.Introduction

➢Motivations

1. Understanding of the relationship between microblog sentiment and stock return is limited due to the lack of consistency and explanation in prior work.

2. In existing studies, microblog sentiment was treated as exogenous when using it to predict stock return, however the endogeneity of microblog sentiment needs investigation.

3. Most related predictive models and empirical studies have treated positive sentiment and negative sentiment equally, and all prior studies have been done at the day level.

1.Introduction

➢Research questions

1. How does microblog sentiment interact with stock return?
2. Do positive sentiment and negative sentiment influence and react to stock return in the same way?
3. Does the relationship between microblog sentiment and stock return differ at the day and hour levels?

1.Introduction

➢Related researches(Market index)

- Bollen et al. (2011) used OpinionFinder (Wilson et al. 2005) to classify Twitter messages as either positive or negative. No significant relationship between the daily polarized sentiment and daily DJIA return was found.

- In another experiment in the same study, Bollen et al. (2011) classified Twitter message sentiment into 6 emotion dimensions: the 3rd lag of the Calm dimension significantly predicts DJIA return. However, there has not been an explanation as to why this relationship exists.

1.Introduction

➢Related researches(Individual Stock)

- Oh and Sheng (2011) forecast individual stock return using sentiment extracted from StockTwits and achieved over 80% in F-measure in predicting the direction of stock price change. However, their results suffer from small sample bias.

- Tirunillai and Tellis (2012) found that both positive and negative reviews influence subsequent daily returns, with the effect of negative reviews being stronger.

- Sprenger et al. (2014) found that sentiment in Twitter messages has a contemporaneous association with individual stock return, but not a predictive relationship.

1.Introduction

➢Innovations

1. **Bidirectional causality.** Treat microblog sentiment as enogenous, and address the bidirectional causality between microblog sentiment and stock return.

2. **Sentiment polarity.** Construct positive sentiment and negative sentiment as two variables in investigating stock return & microblog sentiment relationship.

3. **Observation time horizon**. Look into the stock return & microblog sentiment relationship at both day level and the hour level.

1.Introduction

➢Contributions

1. Examine the relationship between microblog sentiment and stock return at different levels, providing a comprehensive understanding of the interaction.

2. Reveal the both statistically and economically significant effect of microblog sentiment on stock return, being particularly practical relevant to intraday and high-frequency traders.

3. The finding on how microblog sentiment reacts to the stock market extends our knowledge on microblog users from the socio-psychological perspective, and adds to our understanding on the behavioral bias of investors.

2.Research design

➢Framework for empirical analysis

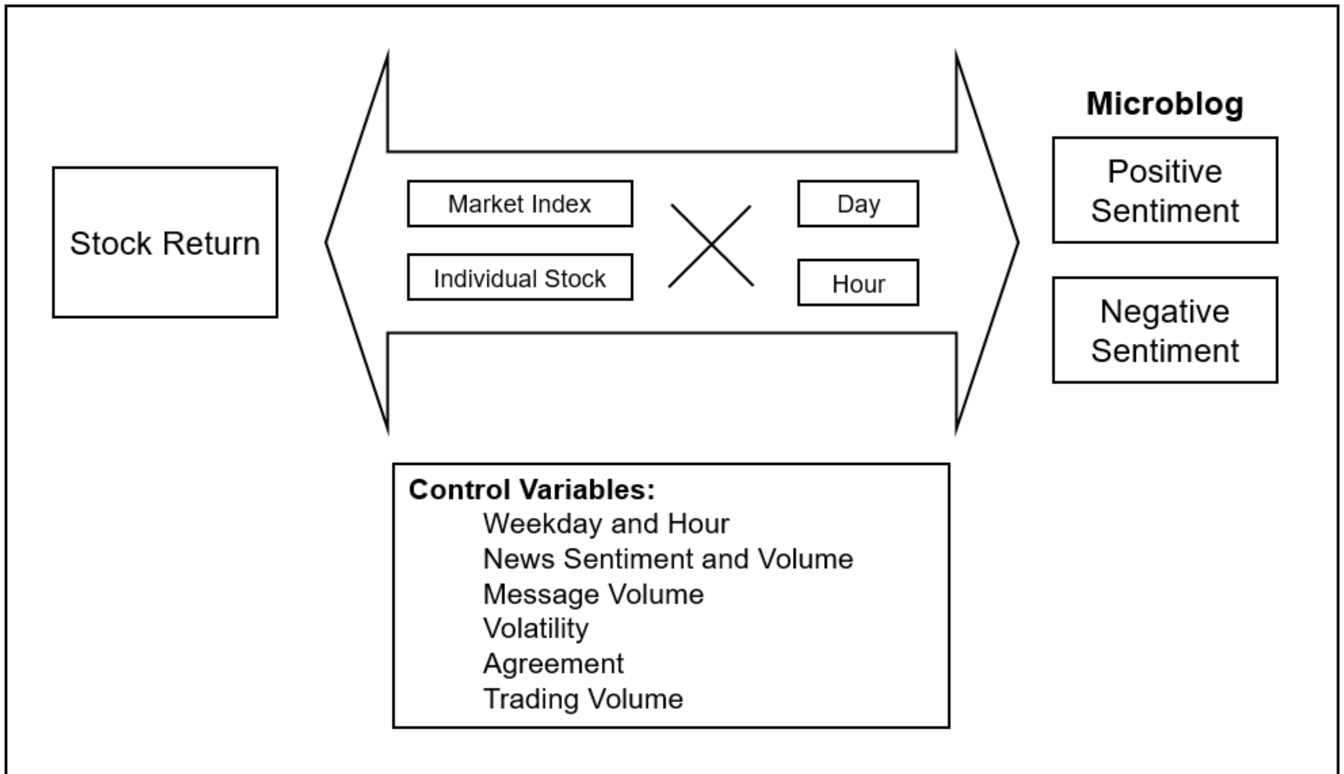


Figure 1. Framework for Empirical Analysis

2.Research design: Data

➢**Period:** 2010.09 – 2014.09

➢**Source:**

- **Microbog Messages :** StockTwits.com
- **News Messages :** reuters.com

➢**Message counts**

- **Microbog Sentiment :** on total 17,835,174 messages; on average over 17,149 articles per day, or 717 articles per hour.
- **News Sentiment :** on average over 3,132 articles per day, or 131 articles per hour.

➢**Tool:** SentiStrength (Thelwall et al. 2010)

➢**Frequency:** daily & hourly

2.Research design: Variables

➢Key Variables (Endogenous)

Return(%)：

Market Index: hourly and daily closing prices of DJIA

Individual Stock: hourly and daily closing prices of 44 selected stock. (more than 10 messages per day, more than 1 billion dollars capitalization)

StockTwits Positive (Negative) Sentiment(%)：

- Step1: Message classified by SentiStrength as positive ,negative or neutral.
- Step2: Positive (Negative) sentiment within a special day (hour) was measured as message number $N_{Positive(Negative)}/N_{Total}$ that day (hour).

2.Research design: Variables

➢Control Variables

Endogenous Variables:

1. **News Sentiment:** word count $N_{Positive}$ - $N_{Nagative}$
2. **News Volume (log)**
3. **StockTwits Message Volume (log)**
4. **Volatility**
5. **VIX:** Chicago Board Options Exchange Volatility Index, for implied Volatility.
6. **Trading Volumn (log)**
7. **Agreement Index (%)**

2.Research design: Variables

➢Control Variables

Exdogenous Variables:

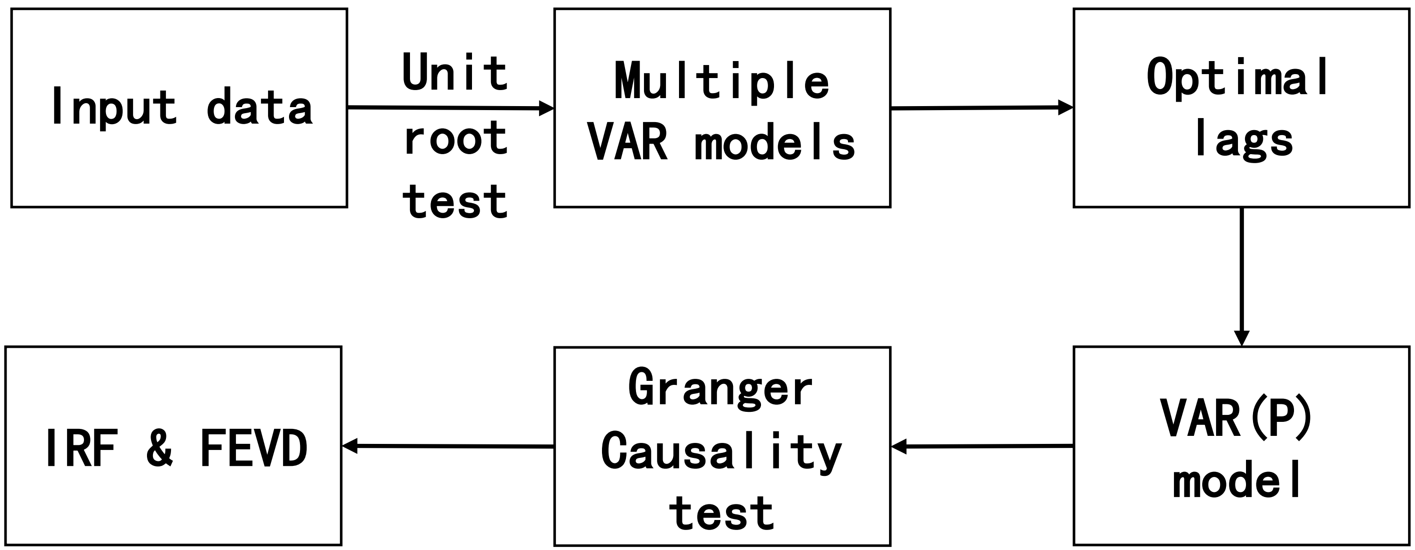
1. **Weekday:** 4 dummies (Tuesday - Friday)
2. **Hour:** 6 dummies: (10AM - 11AM,…, 3PM – 4PM)
3. **FOMC**: 1 dummy: dates of federal open market committee meetings (index level)
4. **PEAD:** 1 dummy**:** post-earnings announcement dates (stock level)

2.Research design: Methods

➢VAR models

Index level: VARX,VAR with exogenous variables

Stock level: PVARX, panel VAR with exogenous variables



2.Research design: Methods

To test the relationship between microblog sentiment and stock return at the market index and day (hour) level, we specify the following model:

$$\begin{bmatrix} Return_t \\ Positive_t \\ Negative_t \\ NewsSentiment_t \\ NewsVolume_t \\ MessageVolume_t \\ Volatility_t \\ VIX_t \\ TradingVolume_t \\ Agreement_t \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \\ C_8 \\ C_9 \\ C_{10} \end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix} \pi_{1,1}^{t-p} & \cdots & \pi_{1,10}^{t-p} \\ \pi_{2,1}^{t-p} & \cdots & \pi_{2,10}^{t-p} \\ \pi_{3,1}^{t-p} & \cdots & \pi_{3,10}^{t-p} \\ \pi_{4,1}^{t-p} & \cdots & \pi_{4,10}^{t-p} \\ \pi_{5,1}^{t-p} & \cdots & \pi_{5,10}^{t-p} \\ \pi_{6,1}^{t-p} & \cdots & \pi_{6,10}^{t-p} \\ \pi_{7,1}^{t-p} & \cdots & \pi_{7,10}^{t-p} \\ \pi_{8,1}^{t-p} & \cdots & \pi_{8,10}^{t-p} \\ \pi_{9,1}^{t-p} & \cdots & \pi_{9,10}^{t-p} \\ \pi_{10,1}^{t-p} & \cdots & \pi_{10,10}^{t-p} \end{bmatrix} \begin{bmatrix} Return_{t-p} \\ Positive_{t-p} \\ Negative_{t-p} \\ NewsSentiment_{t-p} \\ NewsVolume_{t-p} \\ MessageVolume_{t-p} \\ Volatility_{t-p} \\ VIX_{t-p} \\ TradingVolume_{t-p} \\ Agreement_{t-p} \end{bmatrix} + \begin{bmatrix} \gamma_{1,u,t} \\ \gamma_{2,u,t} \\ \gamma_{3,u,t} \\ \gamma_{4,u,t} \\ \gamma_{5,u,t} \\ \gamma_{6,u,t} \\ \gamma_{7,u,t} \\ \gamma_{8,u,t} \\ \gamma_{9,u,t} \\ \gamma_{10,u,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \\ \varepsilon_{7,t} \\ \varepsilon_{8,t} \\ \varepsilon_{9,t} \\ \varepsilon_{10,t} \end{bmatrix}$$

P is the max lag determined by BIC, π_{ij}^{t-p} is the effect of Endogenous Variable j at Time $t-p$ on Endogenous Variable i at Time t, $\gamma_{i,u,t}$ is the effect of Weekday (&hour) u on Endogenous Variable i at Time t.

2.Research design: Methods

To test the relationship between microblog sentiment and stock return at the individual stock and day (hour) level, we specify the following model:

$$\begin{bmatrix} Return_{i,t} \\ Positive_{i,t} \\ Negative_{i,t} \\ NewsSentiment_{i,t} \\ NewsVolume_{i,t} \\ MessageVolume_{i,t} \\ Volatility_{i,t} \\ VIX_{i,t} \\ TradingVolume_{i,t} \\ Agreement_{i,t} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \\ C_8 \\ C_9 \\ C_{10} \end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix} \boxed{\begin{matrix} \pi_{1,1}^{t-p} & \cdots & \pi_{1,10}^{t-p} \\ \pi_{2,1}^{t-p} & \cdots & \pi_{2,10}^{t-p} \\ \pi_{3,1}^{t-p} & \cdots & \pi_{3,10}^{t-p} \end{matrix}} \\ \begin{matrix} \pi_{4,1}^{t-p} & \cdots & \pi_{4,10}^{t-p} \\ \pi_{5,1}^{t-p} & \cdots & \pi_{5,10}^{t-p} \\ \pi_{6,1}^{t-p} & \cdots & \pi_{6,10}^{t-p} \\ \pi_{7,1}^{t-p} & \cdots & \pi_{7,10}^{t-p} \\ \pi_{8,1}^{t-p} & \cdots & \pi_{8,10}^{t-p} \\ \pi_{9,1}^{t-p} & \cdots & \pi_{9,10}^{t-p} \\ \pi_{10,1}^{t-p} & \cdots & \pi_{10,10}^{t-p} \end{matrix} \end{bmatrix} \begin{bmatrix} Return_{i,t-p} \\ Positive_{i,t-p} \\ Negative_{i,t-p} \\ NewsSentiment_{i,t-p} \\ NewsVolume_{i,t-p} \\ MessageVolume_{i,t-p} \\ Volatility_{i,t-p} \\ VIX_{i,t-p} \\ TradingVolume_{i,t-p} \\ Agreement_{i,t-p} \end{bmatrix} + \begin{bmatrix} \gamma_{1,u,t} \\ \gamma_{2,u,t} \\ \gamma_{3,u,t} \\ \gamma_{4,u,t} \\ \gamma_{5,u,t} \\ \gamma_{6,u,t} \\ \gamma_{7,u,t} \\ \gamma_{8,u,t} \\ \gamma_{9,u,t} \\ \gamma_{10,u,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \\ \varepsilon_{6,t} \\ \varepsilon_{7,t} \\ \varepsilon_{8,t} \\ \varepsilon_{9,t} \\ \varepsilon_{10,t} \end{bmatrix}$$

This model looks identical to Model 1, but it uses a different estimation method, general method of moments (GMM) to account for the panel data.

3.Empirical result

➢Coefficients Estimates of the Key Variables:

Table 1. Coefficient Estimates: the effect of sentiment on return

Impulse	Response: Return			
	Market		Stock	
	Daily	Hourly	Daily	Hourly
Positive				
Lag 1	0.0468	0.0056	0.0010	0.0000
Lag 2	0.0171	0.0003	-	-
Lag 3	-0.0372	-0.0021	-	-
Lag 4	0.0163	-0.0006	-	-
Lag 5	-0.1201	0.0009	-	-
Lag 6	-	0.0029	-	-
Lag 7	-	0.0002	-	-
Negative				
Lag 1	-0.0099	-0.0225***	-0.0013	-0.0028***
Lag 2	-0.0570	0.0040	-	-
Lag 3	0.0471	-0.0002	-	-
Lag 4	0.0023	0.0025	-	-
Lag 5	0.0966	-0.0012	-	-
Lag 6	-	0.0058**	-	-
Lag 7	-	0.0014	-	-

On hour level, Negative sentiment lags' effect on both market and individual stock return was implied.

3.Empirical result

➢Coefficients Estimates of the Key Variables:

Table 2. Coefficient Estimates: the effect of return on sentiment

Impulse	Response							
	Market				Stock			
	Daily		Hourly		Daily		Hourly	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
Return								
Lag 1	0.1332**	-0.2997***	0.1980	-0.2784***	0.0921***	-0.2565***	0.2189***	-0.3314***
Lag 2	-0.0018	-0.0694	-0.0457	-0.2410**	-	-	-	-
Lag 3	-0.0057	0.0229	-0.0545	-0.1384	-	-	-	-
Lag 4	0.0677	-0.0260	0.1025	-0.0875	-	-	-	-
Lag 5	-0.0541	0.0958**	0.0217	-0.1230	-	-	-	-
Lag 6	-	-	0.2642	-0.0942	-	-	-	-
Lag 7	-	-	-0.0148	0.0225	-	-	-	-

Effect of lagged market return on Negative sentiment on both Day and Hour level was implied. For individual stock level, return potentially influence sentiment of both kind in both time level.

3.Empirical result—Index

For the return equation , the first and sixth lags of negative sentiment are statistically significant with different sign(-,+), suggesting an overreaction pattern on Index-Hour level.

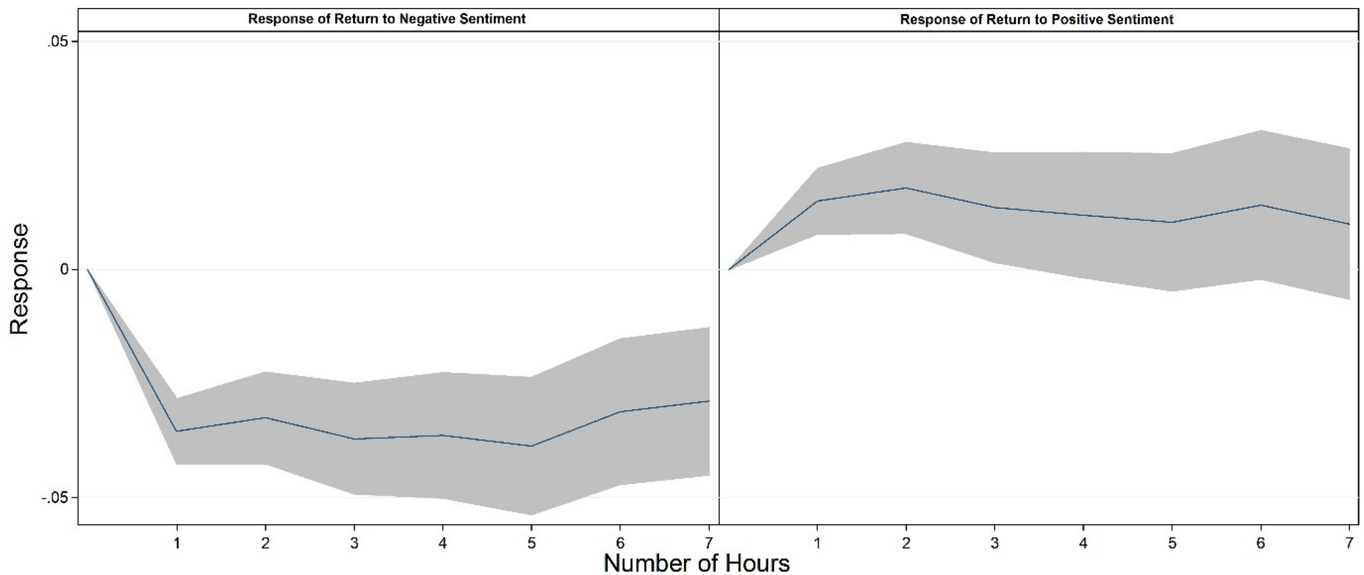


Figure 4. Impulse Response Function: Responses of Return to Negative and Positive Sentiment (Index-Hour)

Negative sentiment significantly Granger causes (χ^2 = 107.55, p < 0.001) return, accounts for up to 1.3% (on Day 7) forecast error of return.

3.Empirical result—Index

For the negative sentiment equation , the first and fifth lags of return are statistically significant with different sign(-,+), suggesting an overreaction pattern on Index-Day level.

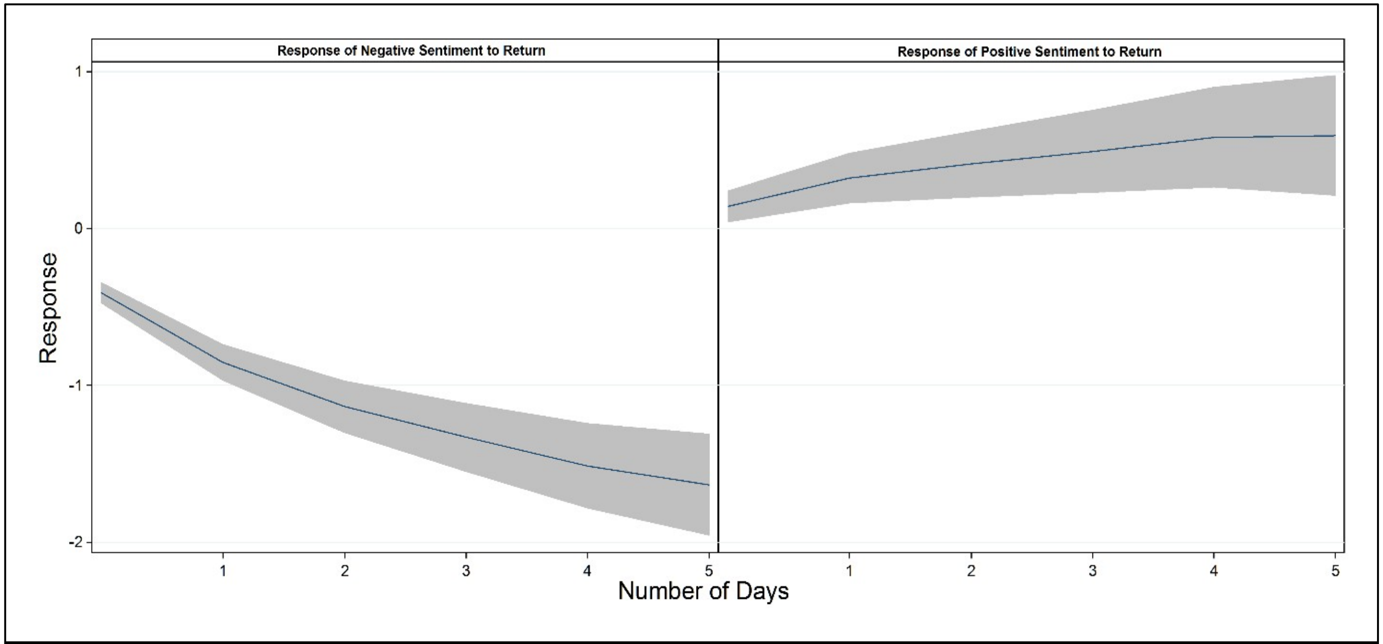


Figure 3. Impulse Response Function: Responses of Negative and Positive Sentiment to Return (Index-Day)

Return significantly Granger causes negative sentiment (χ^2 = 47.21, p < 0.001), accounts for up to 26.8% (on Day 5) forecast error of negative sentiment..

3.Empirical result—Index

For the negative sentiment equation , the first and second lags of return are statistically significant with same sign(-,-) on Index-Hour level.

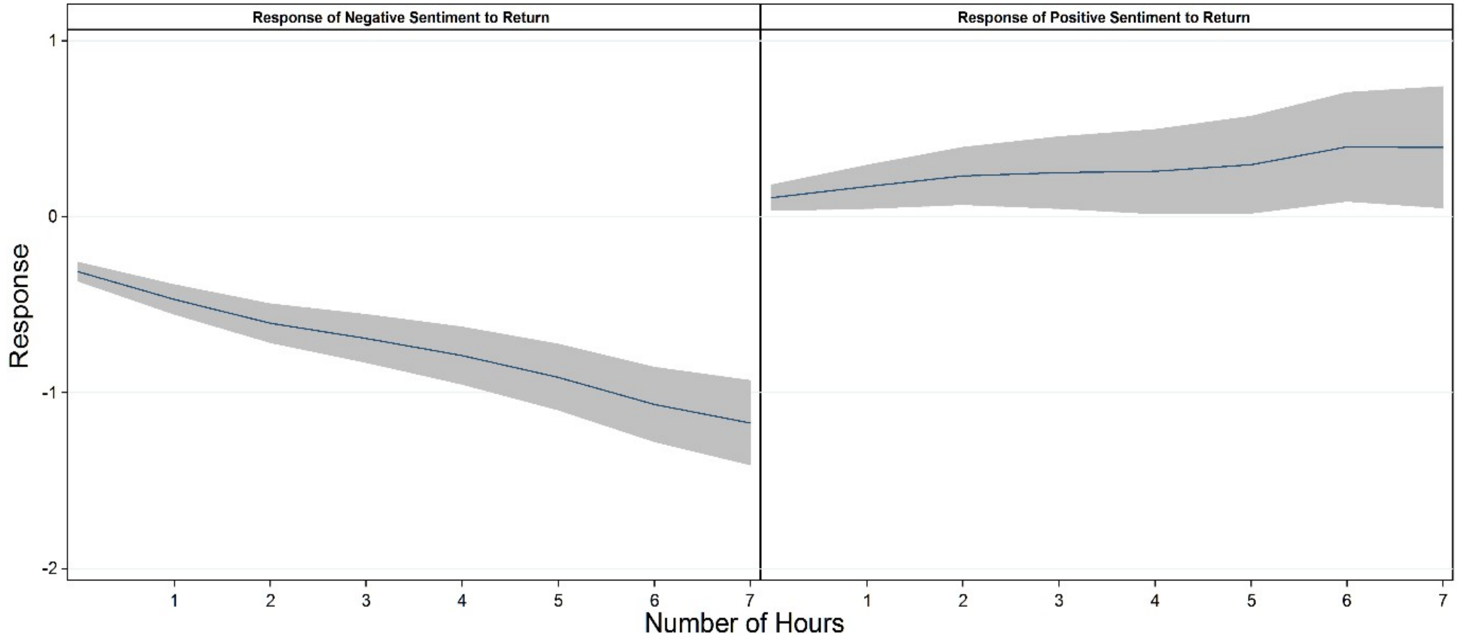


Figure 5. Impulse Response Function: Responses of Negative and Positive Sentiment to Return (Index-Hour)

Return significantly Granger causes negative sentiment (χ^2 = 20.07, p < 0.001), accounts for up to 3.9% (on Day 7) forecast error of negative sentiment..

3.Empirical result—Panel

For the Return equation , the first lag of Negative Sentiment is statistically significant on Panel-Hour level.

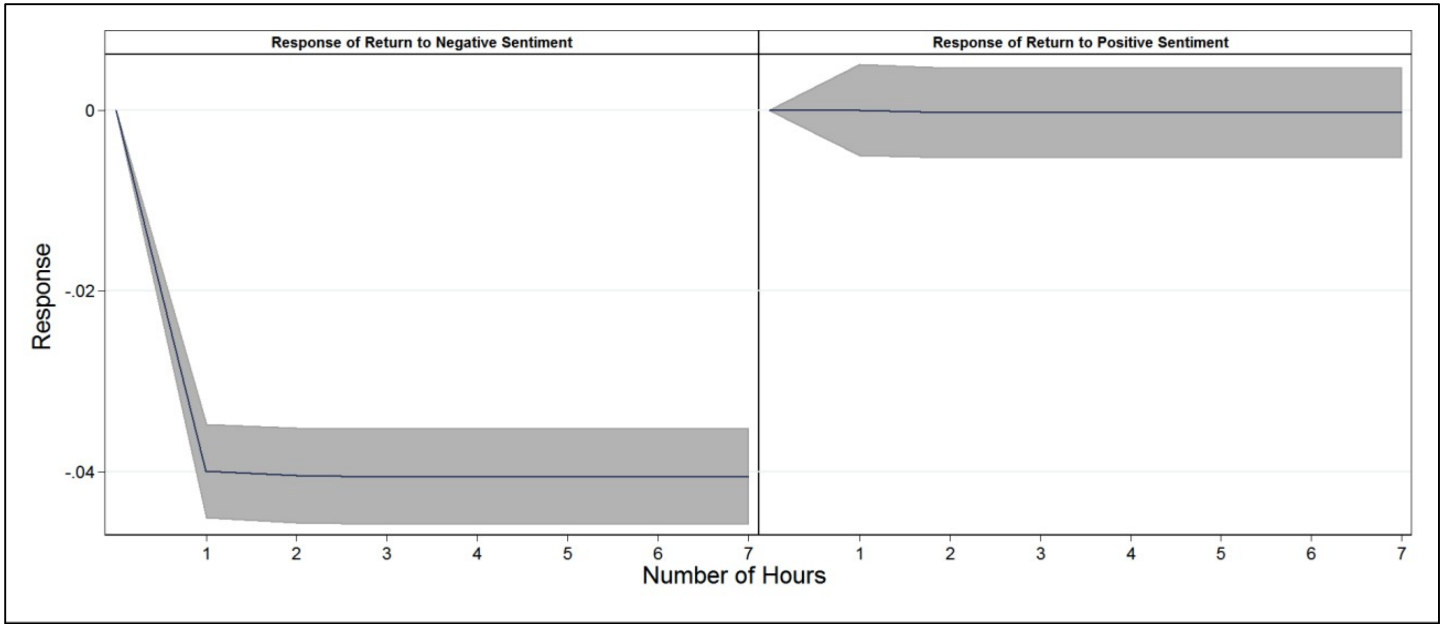


Figure 8. Impulse Response Function: Responses of Return to Negative and Positive Sentiment (Stock-Hour)

Negative sentiment significantly Granger causes (χ^2 = 232.99, p < 0.001) return, accounts for less than 1% forecast error of return, weaker than market level.

3.Empirical result—Panel

For both the Positive Sentiment and Negative Sentiment equation , the first lag of return is statistically significant on Panel-Day level.

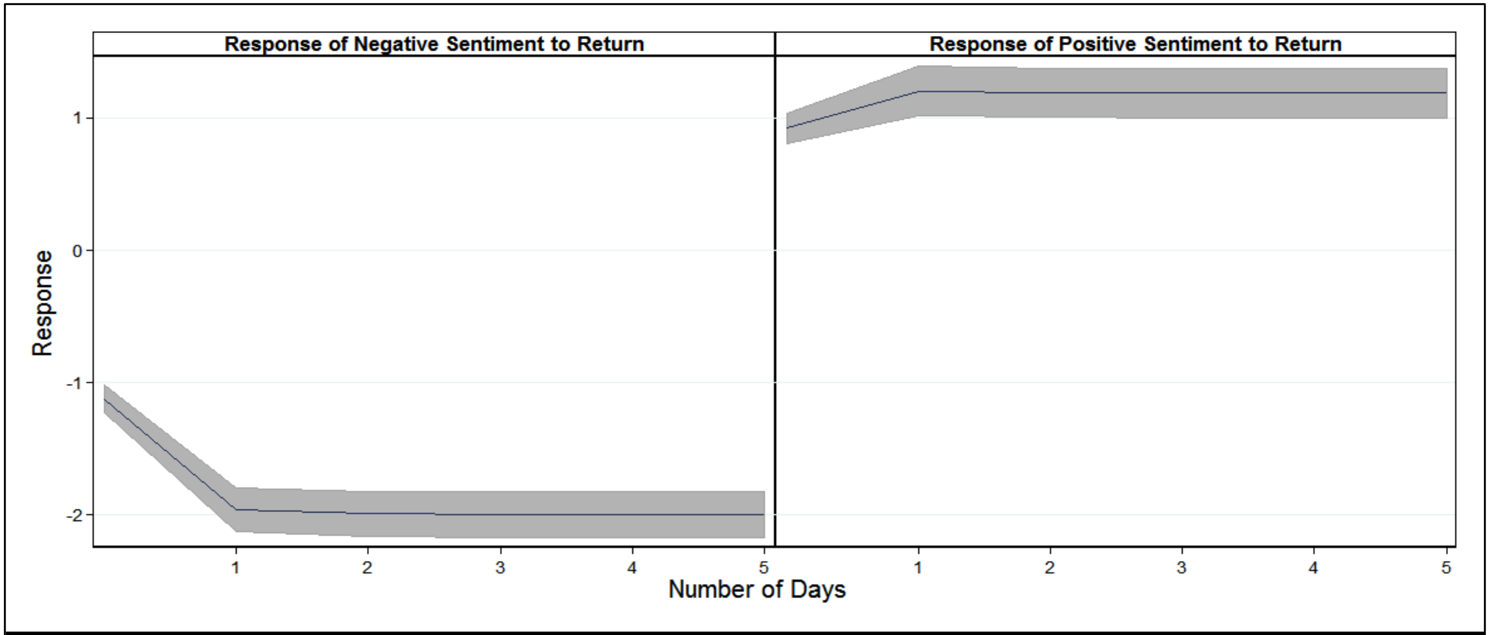


Figure 7. Impulse Response Function: Responses of Negative and Positive Sentiment to Return (Stock-Day)

Granger causality tests show that return influences both positive (χ^2 = 21.50, p < 0.001) and negative sentiment (χ^2 = 190.00, p < 0.001), with a larger effect on negative sentiment. Both effects diminishing quickly in following days

3.Empirical result—Panel

For both the Positive Sentiment and Negative Sentiment equation , the first lag of return is statistically significant on Panel-Hour level.

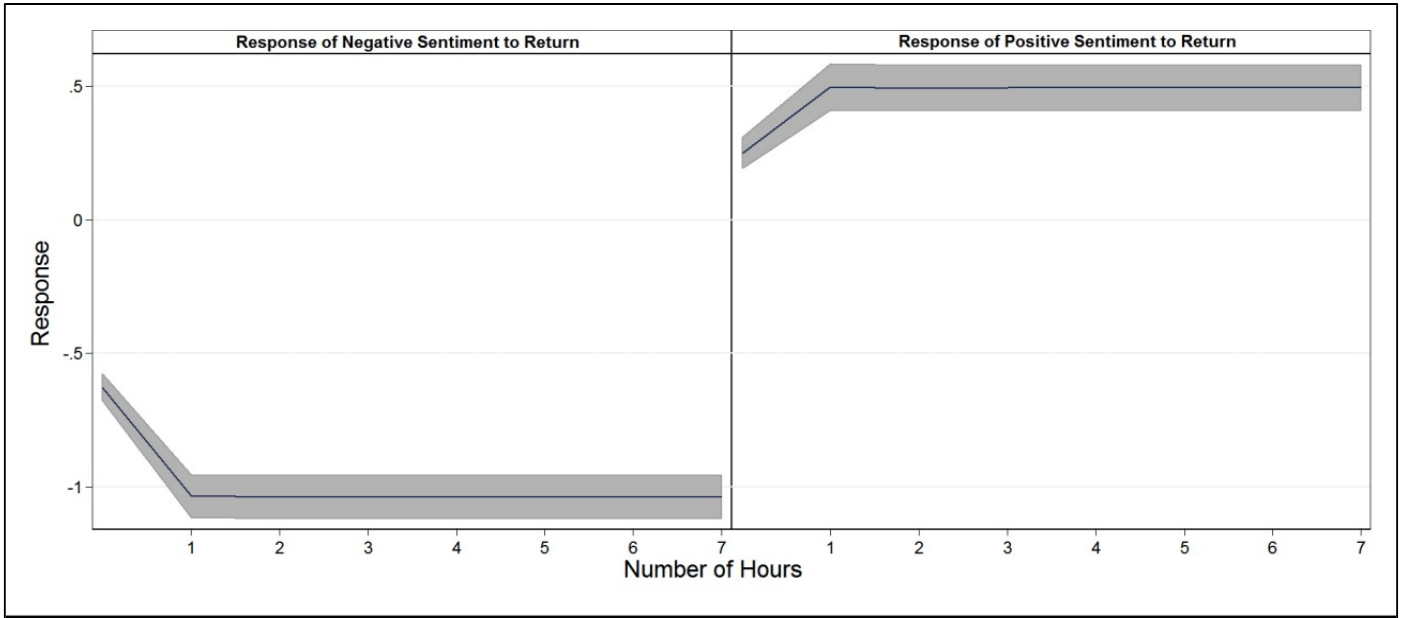


Figure 9. Impulse Response Function: Response of Negative and Positive Sentiment to Return (Stock-Hour)

Granger causality tests show that return influences both positive (χ^2 = 80.45, p < 0.001) and negative sentiment (χ^2 = 160.57, p < 0.001), with a larger effect on negative sentiment.

4.Conclusion

1. Only Negative sentiment significantly influences stock return over a shorter time horizon (hour), and not over a longer horizon (day).

2. Microblog sentiment is also largely driven by movement in the market. Moreover, stock return has a stronger influence on negative sentiment than on positive sentiment.

3. The effect of stock return on microblog sentiment is much stronger and exists longer at the market level than at the stock level.

Appendix

➢Limitations & Future Directions

1. In panel models, only large companies with frequent microblog (44) mentions were studied, thus findings may only pertain to such companies. (Larger panel)

2. The sentiment classification based on current sentiment analysis tool is not perfect. (higher accuracy & more dimensions)

3. The predictive power of microblog sentiment on the stock return is subject to malicious manipulations. (social media market manipulation detection)