

METU

ALPEREN AYDIN

Table of Contents

1. ABSTRACT	3
2. INTRODUCTION	3
3. LITERATURE REVIEW	4
4. DATA AND METHODOLOGY	5
5. CONCLUSION.....	9
6. APPENDIX	10
7. REFERENCES	11

1. ABSTRACT

This study examines the effect of online forums, Investing.com, on aggregate individual investors' behavior. We gather comments from Investing.com forum of Tesla in February 2025 and implement Hugging Face's zero-shot classifier to tag each comment as bullish, bearish or neutral. After we get score of each comment, we try to capture any effect on the Tesla Close Price and Volume in February 2025. Running a hourly OLS regressions with control variables, we find that sentiment score of comments is not statistically significant on Tesla's price or volume.

2. INTRODUCTION

People usually share their investing ideas with “not investment advice” warning. Even people statistically talk about some investing tools like stocks, they may need to state that it is not investment advice or in some countries it is compulsory to mention it. Do aggregate people thoughts on internet really affect other people investing behaviour? Even if some platforms like Twitter, Reddit effects are investigated, any investing platform effect is not investigated.

Prior studies showed that social media sentiment can forecast short-term market moves. Twitter mood or Reddit comment volume can give an idea about the market future moves. However, these findings are mainly focused on the social media. There is a gap where most of the users are investors.

To fill this gap, we collect comments posted on Investing.com Tesla forum during February 2025. Since there is plenty of comments, we use Hugging Face's zero-shot BART-MNLI classifier to label each as bullish, bearish, or neutral. We grouped the comments by hourly as

total number of comments and average score of sentiment score. To capture any effect, we run OLS with Tesla's hourly close prices and trading volume.

We could not find a statistically significant relationship between sentiment score of comments and nor Tesla's price nor Tesla's volume. With different models, still number of comments and sentiment score have performed poorly.

3. LITERATURE REVIEW

Bollen, Mao, and Zeng (2011) investigated the use of Twitter mood indicators to forecast market movements in the Dow Jones Industrial Average. By analyzing millions of tweets to measure overall public mood, they showed that when people's feelings shift, the stock market tends to react a few hours later. Follow-up work by Zhang et al. (2011) extended this framework to individual equities, showing that tweets that are more positive or negative help explain price changes within the day, even after taking into account yesterday's price moves. These findings show that you can get reliable, immediate clues about market sentiment by analyzing huge amounts of social-media data and people's online moods reflected in stock prices also sometimes those moods are strong enough to move the market itself.

Antweiler and Frank (2004) examined text from Yahoo! Finance message boards and found that both the volume and tone of posts have a statistically significant impact on next day volatility and returns for individual stocks. Their regression models included control variables such as market index returns and trading volume yet showed that what people said on the forums related for a noticeable big portion of the price movement that happened overnight. Subsequent research (e.g. Li et al., 2018) refined these methods by distinguishing between expert versus amateur posters. Overall, these studies suggest that when traders gather to talk about a specific stock, even small changes in mood or activity can lead to real, measurable effects on that stock's price.

Lately, researchers have started looking at specialized trading platforms where the conversation is all about deciding to buy or sell. Syed and Sprenger (2011) studied StockTwits and showed that sudden spikes in bullish or bearish hashtags show up just before quick price changes in those stocks. Their event-study approach revealed that ,even after accounting for

trading usual noise, concentrated bursts of trader-focused language serve as an early warning signal. Similarly, Chen et al. (2022) employed a fine-tuned BERT model on r/WallStreetBets posts, demonstrating that not only the direction but also the intensity of sentiment improves one-hour ahead return forecasts for heavily traded technology equities. These studies highlight that focused trading communities can give clearer and quicker clues about market sentiment than general social media channels.

4. DATA AND METHODOLOGY

We collect two primary datasets. First, we get 4 880 comments publicly posted on the Investing.com forum. For each comment, the data consist of the timestamp and the user name. Second, we obtained TSLA hourly closing prices and trading volumes in python with yfinance for February 2025.

Given the volume of comments, we employed a classifier to assign sentiment labels automatically. Specifically, we used Hugging Face’s zero-shot BART-MNLI model to categorize each comment as bullish, bearish, or neutral, and to generate a corresponding sentiment score. These labels were recorded numerically as +1 for fully bullish, -1 for fully bearish, and 0 for neutral. For example, the user Henrique BG posted “People don’t realize that no revenue leads to shares drop every day, towards the dust,” on 28 February 2025 at 21:24, which the model scored at -0.9469.

To prepare our data for regression, we first match the each comment’s timestamp with the Nasdaq trading schedule. Comments posted during these market hours were assigned to their corresponding hourly interval directly. For comments that fell outside of trading hours, including overnight, weekend, and holiday posts, we redistributed them equally across the first three trading hours of the next open session. Concretely, if x comments occurred outside market hours on a given calendar day, we added $x/3$ comments to each of the 09:30–10:30, 10:30–11:30, and 11:30–12:30 EST intervals on the next trading day. Thus, we had the regression:

Hypothetical regression (1):

$$r_t = \beta_0 + \beta_1 SC + \beta_2 CN + \varepsilon_t$$

Where,

r_t : asset return in hour t ($\ln(P_t) - \ln(P_{t-1})$)

SC: average comment score in hour t

CN: number of comments in hour t

ε_t : error term

After we run the OLS regressions, we get:

Model.1 :

$$r_t = -0.0029 + 0.0012SC + 0.00003739CN + \varepsilon_t$$

(-1.577) (0.916) (0.405)

(values given in parenthesis are t values)

R squared:	0.007
Adj. R squared:	-0.009
F statistic:	0.4540
Jarque-Bera (JB)	200.090
AIC:	730.4

The average comment score and the number of comments explain almost nothing about the asset return. We cannot reject either the individual coefficient t stat or joint significance, so they are not statistically significant. The effects of the variables are so small on the asset return.

The Jarque–Bera test rejects the normality of residuals, while the Durbin–Watson statistic suggests no serious autocorrelation.

Thus, comment volume and average sentiment score do not exhibit a consistent or meaningful influence on TSLA's hourly returns.

Hypothetical regression (2):

$$\Delta V_t = \beta_0 + \beta_1 SC + \beta_2 CN + \varepsilon_t$$

Where,

ΔV_t : log change in volume in hour t

Model.2:

$$\Delta V_t = 0.1784 + 0.0725 SC + 0.0039 CN + \varepsilon_t$$

(1.110)	(1.089)	(0.269)
---------	---------	---------

R squared:	0.009
Adj. R squared:	-0.006
F statistic:	0.5972
Jarque-Bera (JB)	522.269
AIC:	423.8

Average comment score and the number of comments cannot explain the volume change but it explains a little better than asset return. We again cannot reject either the individual coefficient t stat or joint significance, so they are also not statistically significant in the volume change model.

The Jarque–Bera test rejects residual normality, and the Durbin–Watson statistic (DW) indicates no major autocorrelation.

Thus, comment volume and average sentiment score do not exhibit a consistent or meaningful influence on TSLA's hourly volume.

Since we had very poor performance on original models, we will add control variables as explanatory variables to our models to see if any change occurs. We will add S&P500 and lagged of r_t .

Hypothetical regression (3):

$$r_t = \beta_0 + \beta_1 SC + \beta_2 CN + \beta_3 SP500 + \beta_4 r_{t-1} + \varepsilon_t$$

where,

r_t : asset return in hour t

SC: average comment score in hour t

CN: number of comments in hour t

SP500: S&P 500 index return in hour t

r_{t-1} : TSLA's return in the previous hour t

ε_t : error term

Model.3:

$$r_t = -0.0027 + 0.0020 \text{ SC} + 0.00003345 \text{ CN} + 2.5911 \text{ SP500} + -0.0649 r_{t-1} + \varepsilon_t$$

(-2.034) (1.454) (0.668) (3.975) (-0.709)

R squared:	0.301
Adj. R squared:	0.278
F statistic:	5.521
Jarque-Bera (JB)	91.311
AIC:	-763.2

The average comment score and the number of comments still have a small effect on asset return. We cannot reject either the individual coefficient t statistic, so they are not still statistically significant but they performed much better than in the first model.

S&P500 is highly significant ($p < 0.001$). A point increase in market return leads to a 2.6-point increase in asset return. However, the lagged return asset is not significant, so yesterday's return doesn't have predictive power.

Adding S&P500 dramatically increased the explanatory power, from zero to $R^2 = 0.301$. Even though this control variable increased the importance of the comment score and comment number, they are neither statistically important nor powerful on asset return.

Hypothetical regression (4):

$$\Delta V_t = \beta_0 + \beta_1 \text{ SC} + \beta_2 \text{ CN} + \beta_3 \text{ SP500} + \beta_4 \Delta V_{t-1} + \varepsilon_t$$

where,

ΔV_t : log change in volume in hour t

ΔV_{t-1} : log change in volume in previous hour t

Model.4:

$$\Delta V_t = -0.0358 + 0.0452SC + 0.0012CN - 30.8779 SP500 - 0.2982\Delta V_{t-1} + \varepsilon_t$$

(-0.510)	(0.701)	(0.599)	(-1.132)	(-4.468)
----------	---------	---------	----------	----------

R squared:	0.111
Adj. R squared:	0.082
F statistic:	6.214
Jarque-Bera (JB)	37.098
AIC:	245.0

The average comment score and the number of comments still have only a small estimated effect on hourly volume change. Individual t-statistics still do not allow us to reject the null hypothesis of zero effect, so both remain statistically insignificant. Although their estimated coefficients are larger than in our original specification, they are not still important predictors of volume change.

In contrary to Model.3, S&P500 return insignificant. This indicates that market returns do not meaningfully predict TSLA's volume changes. By contrast, the lagged volume change term is highly significant ($p < 0.001$), showing strong autocorrelation in hourly trading volume.

Overall, adding these control variables raises the model's explanatory power from essentially zero to $R^2 = 0.111$. However, the model again lacks statistical or economic significance in explaining volume fluctuations.

5. CONCLUSION

None of our models show a meaningful role for Investing.com forum activity in predicting TSLA intraday behavior. In the baseline return model, comment count and comment score both had small coefficients and non-significant t-values. The volume-change model was equally uninformative.

When we added controls ,S&P500 return and the one hour lag of TSLA, the asset return model's explanatory strength rose noticeably. Even then, the volume of forum comments and

their average sentiment remained unable to explain any of Tesla's price moves. Likewise, our volume-change model showed a bit better performance once we accounted for market return and past trading patterns, but again, the average sentiment and comments was still statistical insignificant.

Even if there are many finance-related users on Investing.com and they share ideas about the stock at the current time, we could not find an effect on aggregate people's beliefs and so on the market. This is not a contradiction of other research but shows the effect of the Investing.com forum.

6. APPENDIX

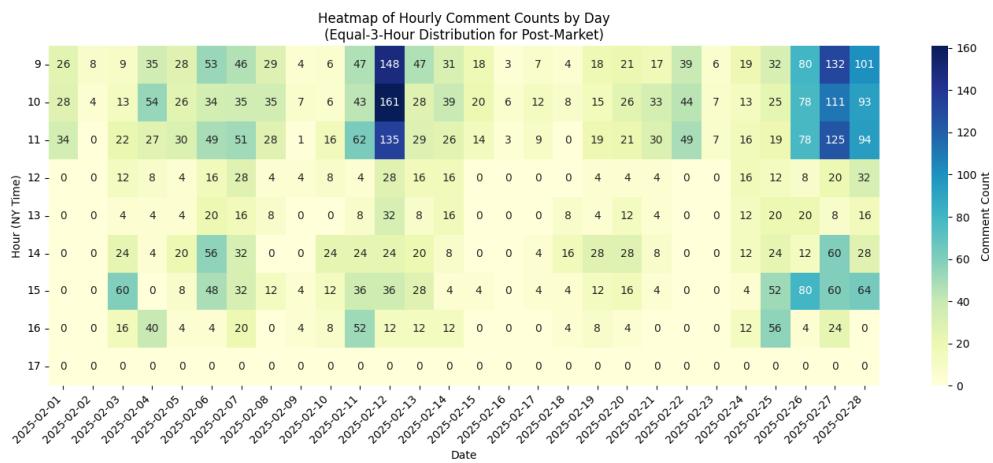


Figure.1

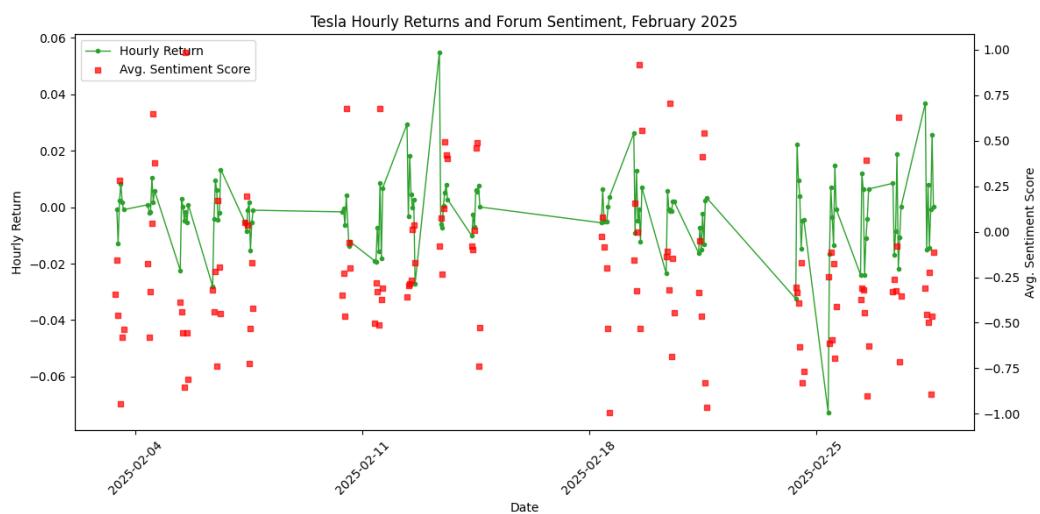


Figure.2

7. REFERENCES

- Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, 59(3), 1259–1294.
- Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1), 1–8.
- Chen, L., Liang, J., & Chen, H. (2022). Forecasting short-term returns with fine-tuned BERT: Evidence from r/WallStreetBets. *Journal of Financial Data Science*, 4(1), 45–58.
- Li, X., Feng, Y., & Chen, H. (2018). Expert vs. amateur sentiment: Distinguishing informational value on financial forums. *Journal of Behavioral Finance*, 19(2), 123–137.
- Syed, M., & Sprenger, T. O. (2011). Social-media sentiment and stock returns: An event-study approach on StockTwits. *Working paper*, University of California.
- Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through Twitter sentiment analysis. *Social Network Analysis and Mining*, 1(1), 1–12.