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Modeling Market Sentiment and Stock Price Dynamics: Evidence from Paytm Post-IPO Trading

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Abstract: - This research paper investigates the correlation between public sentiment on social media and the stock price of Paytm from February 1 to February 16, 2024. By employing sentiment analysis, the study aims to explore how public opinion, expressed through platforms like Twitter, affects Paytm's stock price movements. We gathered a dataset of relevant tweets and used natural language processing (NLP) to categorize the sentiments expressed as positive, negative, or neutral. At the same time, we analyzed Paytm's stock price data from the same period to explore any meaningful connections between the sentiments and stock performance. The results could provide valuable insights for investors, stakeholders, and companies aiming to better understand how public sentiment influences market behavior.

Key terms: Public Sentiment, Stock Price Reaction, Sentiment Analysis, Paytm, Behavioral Finance, Investor Behavior, Stock Market Volatility, Natural Language Processing (NLP), Social Media Analytics, Post-IPO Analysis, Financial Markets

1. INTRODUCTION

The internet and social media platforms like X, Facebook and Reddit have changed the way we share information and are public spaces for discourse. Sentiment analysis which looks at opinions, emotions and attitudes in text has become a tool for researchers, businesses and governments to extract insights from this vast pool of user generated content (Sánchez-Rada & Iglesias, 2019). Machine learning models have proven to be effective in sentiment classification and decision making such as detecting fake reviews (Jain et al., 2021b).

The rise of social media in financial opinion sharing has led to studies linking online sentiment to stock market trends. Twitter with its real time and accessible content has become the primary platform for sentiment analysis. For example, Asur and Huberman (2010) predicted movie box office earnings using Twitter sentiment, while Bollen, Mao and Zeng (2011) showed the predictive power of public mood in forecasting Dow Jones Industrial Average trends. Advanced models like LSTM and Neural Prophet have further improved accuracy with the latter reducing RMSE by 25% and MAE by 20% (Koolwal, 2024). Other studies like the ones on Adani Group stocks have shown how events impact market sentiment and stock prices (Iniyan et al., 2024).

Twitter sentiment analysis employs machine learning and NLP techniques such as Support Vector Machines (SVM), Naive Bayes, and deep learning models like LSTM, which have achieved classification accuracy up to 84% (Sengaliappan & Anbarasan, 2024). Hybrid approaches, like combining SVM with CNN or ensemble methods like Voting Classifiers, have enhanced prediction robustness (Pal & Bhushan, 2024).

In India, One97 Communications Ltd., known for its Paytm app, epitomizes digital innovation in financial services. Despite its significant growth, including launching Paytm Payments Bank to enhance financial inclusion (Sharma et al., 2024), Paytm's IPO faced negative sentiment. Research highlighted that negative tweet outnumbered positive ones nearly two-to-one (Mehta et al., 2022). Regulatory hurdles, such as the RBI's directive that restricted Paytm's lending arm from accepting new deposits, heightened investor worries and led to a 20% drop in the company's shares (HT News Desk, 2024).

These findings highlight the importance of sentiment analysis in understanding consumer and investor behaviour, especially in response to events like regulatory setbacks. By analysing Twitter data from February 1 to 16, 2024, the study explored public sentiment regarding Paytm's stock performance after the RBI's decision. It sheds light on how public opinion intersects with market trends, showcasing sentiment analysis as both a predictive and diagnostic tool.

2. LITERATURE REVIEW

Public sentiment and financial markets have been in the spotlight lately with social media playing a big role in expressing opinions. Studies have shown that social media sentiment can predict stock market trends. For example, Komariah et al (2016) found 65.7% correlation between Twitter sentiment and currency exchange rates supporting semi-strong market efficiency. Similarly, Bollen et al (2011) linked Twitter sentiment to Dow Jones Industrial Average (DJIA) fluctuations during market volatility.

Paytm, a leading player in India's digital payment space, is a good example of how sentiment analysis plays out in financial events. After RBI directive on its lending arm, negative social media sentiment coincided with stock price drop (HT News Desk, 2024). This shows how public mood affects stock performance as per efficient market

theory (Zhang et al, 2011).
Sentiment analysis uses various methods from statistical models to machine learning. NLP advancements have improved its performance with techniques like CNN-LSTM combination giving better accuracy (Shah, 2023). But challenges persist like noisy data and bias in sentiment interpretation and need critical analysis and additional data sources (Wankhade et al., 2022).
Despite the limitations, sentiment analysis gives financial insights. Future frameworks and methods will only make it more precise and help with better decision making in financial markets.

3. RESEARCH METHODOLOGY

Data Collection

Twitter Data Collection - Twitter, a popular microblogging platform, allows users to share thoughts on various topics (Alsaeedi & Khan, 2019; Bhattacharya, 2021). For this study, tweets about Paytm were collected following the Reserve Bank of India's January 29, 2024, directive prohibiting Paytm Payments Bank from accepting new deposits. Tweets spanning February 1–16, 2024, were retrieved using Twikit, Python library for accessing Twitter API.
Relevant tweets were gathered using specific keywords and hashtags tied to the Paytm crisis, such as #paytmcrisis, #paytmmatkaro, #paytmfraud, #uninstallpaytm, #banpaytm, #paytmkaro, #paytmpaymentbank, and #trustpaytm, ensuring focused data collection on public reactions.
Stock Price Data Collection - Paytm's daily stock price data was downloaded directly from the official NSE India website. The stock data was collected for the period from February 1 to February 16, 2024, to coincide with the sentiment data collected from Twitter. This period was chosen to analyse the immediate market impact following the RBI's restrictions on Paytm's lending arm.

Data Pre-Processing

The Twitter data collected was carefully pre-processed to prepare it for analysis and extraction of meaningful insights. This step is essential to filter out irrelevant information and ensure the results are accurate and reliable. The pre- processing involved several tasks, such as removing URLs, user mentions, special characters, and numbers, as well as eliminating duplicates, retweets, and non-English content. Additionally, the text was normalized through tokenization and lemmatization to make it suitable for analysis.

Sentiment Analysis of Tweets

To study user feelings, VADER as sentiment analysis tool was applied. VADER is a common rule-based means of social media content analysis due to its ability to measure targeting sentiment intensity (Bonta & Janardhan, 2019).
Custom Lexicon: Due to the fact that standard VADER lexicon does not seem to carry boundaries over sentiments related to Paytm, we expanded the lexicon with event related words. For example, words "crisis", "ban", "boycot" were deprived of a less positive sentiment score while words "supportpaytm" were assigned positive scores to them. This tailoring of the method made sentiment classification more context suitable.
Sentiment Scores: Every tweet that was analysed was rated using VADER tool which gives out 4 metrics – Positive, Neutral, Negative and Compound. To describe each of the major sentiments above, the Compound score was used, it is the normalized score from -1 where it is negative to +1 which is the positive score.
Null Hypothesis 1: Daily sentiment scores do not Granger-cause daily stock returns.
Null Hypothesis 2: Daily stock returns do not Granger-cause daily sentiment scores.

1.	score > 0	Positive
2.	score < 0	Negative
3.	score = 0	Neutral

Formulation of Hypotheses

This study is grounded in the principles of behavioral finance and the Efficient Market Hypothesis (EMH), proposing that public sentiment shared on social media platforms like Twitter plays a role in shaping stock market performance. The hypotheses are as follows:
Null Hypothesis (H0): There is no significant correlation between Twitter sentiment (as measured by sentiment scores) and Paytm's stock returns.
Alternative Hypothesis (H1): There is a significant correlation between Twitter sentiment and Paytm's stock returns.

Statistical Analysis

Correlation Analysis

To assess the relationship between public sentiment and Paytm's stock price, a Pearson Correlation Coefficient analysis was performed between the daily average sentiment score and the daily stock returns. This analysis aimed to determine if changes in sentiment were significantly correlated with changes in Paytm's stock price during the study period.

4. RESULTS

4.1 Sentiment Analysis

Overall Sentiment Polarity: The overall compound score for the dataset is -0.50. This score is significantly negative, meaning that most of the tweets in your dataset expressed negative sentiment toward Paytm during the analyzed event. A score of
-0.50 indicates a moderate to strong negative sentiment across the data.
Overall Sentiment: Based on the overall compound score, the sentiment of the dataset is classified as "Negative."
The negative sentiment indicated by the (- 0.50) compound score suggests that most users on social media were expressing discontent, frustration, or anger towards Paytm after Reserve Bank of India prohibition of Paytm lending
The correlation coefficient r ranges from1 to +1. The following guidelines were used to interpret the strength of the correlation:

1.	0.00 ≤ |r| < 0.300	Weak correlation
2.	0.30 ≤ |r| < 0.500	Moderate correlation
3.	0.50 ≤ |r| ≤ 1.000	Strong correlation

Granger Causality Test

It is a statistical test used to check whether one time series can predict another. It does not imply a direct cause-and-effect relationship but rather whether past values of one variable contain information that helps forecast another. The Granger causality test was conducted to determine if daily sentiment scores Granger-cause Paytm's daily stock returns and vice versa. The test was performed using a VAR system with a lag order of 1.

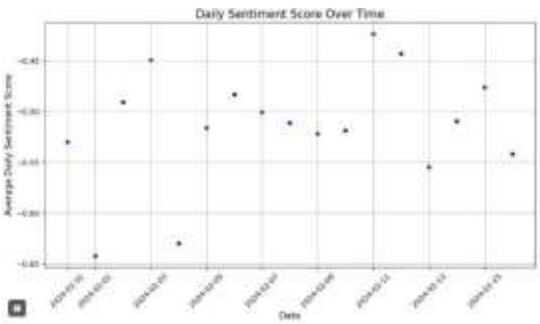

Figure 1: Daily Sentiment score over days

4.2 Correlation Coefficient analysis

The results of the analysis are as follows:

- Pearson Correlation Coefficient: 0.5587
- P-value: 0.0472

This indicates a moderate positive correlation between the sentiment from Twitter and Paytm's daily stock returns. The p-value of 0.0472 confirms that this correlation is statistically significant. The positive correlation (0.5587) suggests that as sentiment improves (becomes more positive), Paytm's stock returns also tend to improve, and vice versa. This supports the hypothesis that public opinion on social media can influence or reflect investor behavior in the stock market. A sentiment score drops, as seen during the period of negative news related to Paytm, coincided with declining stock performance.

Figure 2: Correlation Matrix

Figure 3: Prominent words in tweets

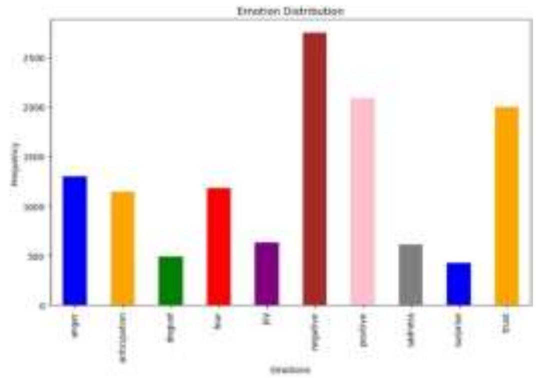

Figure 4: Bar graph of emotions related to Paytm

Anger, fear, and sadness are notably present, which can be tied to users' dissatisfaction and frustration towards Paytm following the Reserve Bank of India's prohibition of its lending services. Words like "crisis," "boycott," and "fraud," which were given higher negative scores in the custom VADER lexicon, likely contributed to these emotions. words associated with negative events were weighted heavily, emotions like **anger**, **fear**, and **sadness** dominate the distribution, reinforcing the overall negative sentiment.

4.3 Granger Causality Test

Equation 1: Daily Sentiment Score as the Dependent Variable

- **Daily Sentiment Score (Lag 1)**: The coefficient is negative but not statistically significant (-0.00010, p=0.5540).
- **Daily Stock Return (Lag 1)**: The coefficient is negative but not statistically significant (-0.3121, p=0.1515).

Equation 2: Daily Stock Return as the Dependent Variable

- **Daily Sentiment Score (Lag 1)**: A positive and statistically significant coefficient (921.549, p=0.0037) suggests that past stock returns positively influence current sentiment scores.
- **Daily Stock Return (Lag 1)**: A positive and statistically significant coefficient (0.5492, p=0.0259) suggests that past stock returns positively influence current sentiment scores.

From the F-tests for zero restrictions:

- **Stock Return Granger-causes Sentiment Score**:

$F(1, 8) = 0.38146$, p-value= [0.5540]: No Significant evidence of causality in this direction.

- **Daily Sentiment Score Granger-causes Stock Return**:

$F(1, 8) = 16.318$, p-value= [0.0037]: Significant evidence that sentiment scores influence stock return.

This supports a **unidirectional causality**: **Sentiment drives Stock returns, but not vice versa**.

5. DISCUSSION

The study highlights the influence of public sentiment on financial decision-making, particularly during critical events affecting a company's operations. Using Paytm as a case study, the research explored the relationship between public opinion, expressed on Twitter, and stock price movements following regulatory restrictions imposed by the Reserve Bank of India. A moderate positive correlation ($r = 0.5587$, p value = 0.0472) was discovered between sentiment scores and Paytm's stock returns, indicating that changes in public sentiment align closely with stock performance. This reinforces the importance of sentiment analysis as a tool for understanding market behavior.

The analysis further revealed that negative sentiments, driven by fear, anger, and sadness, dominated public discourse during the crisis. This finding underscores the reactive nature of public opinion and its potential to amplify market volatility in response to adverse developments.

From the Granger Causality Test, it was ascertained that the influence underlying the association between sentiment and stock returns followed a particular direction. It follows from our findings that sentiment scores Granger-cause stock returns ($F(1, 8) = 16.318$, $p = 0.0037$), thus establishing a unidirectional causality. On the other hand, there is no strong evidence that stock returns Granger-cause sentiment scores $F(1, 8) = 0.38146$, $p = 0.5540$. This confirms the hypothesis that, although people's sentiment is a strong driver of stock prices, the relationship works not the other way round. These findings are at odds with the more prevalent view that sentiment is the main driver of stock returns dynamics, and suggest more complex causal relationships, with sentiment being the main predictor of stock returns.

The study's results reiterate the need for integration of sentiment analysis into market strategy and decision-making frameworks. Additionally, these conclusions show that from a practical standpoint social media site such as Twitter can alert businesses and investors in real – time to act and manage brand perception. For investors, the analysis enhances understanding of the relation between sentiment and stock returns from a dual perspective that also proves difficult to manage during volatile times for the security markets. For firms, understanding how the public sentiment shifts during crises and managing the negativity would help in maintaining the faith of the investors and the stock price performance during difficult times. Future work may enrich these results by focusing on industry differences, incorporating sentiments across several platforms and using time series models to look closer to the nature of the relationship between stock prices and investor opinions. The analysis concludes that the real – time analysis of public opinion provides the businesses with adequate time to respond proactively to changes in sentiment thus enabling the projection of the impact of brand strategies and losses that could arise. Companies can leverage these tools to manage brand perception and mitigate the impact of adverse sentiment.

6. LIMITATIONS AND FUTURE SCOPE

6.1 Limitations of the Study

Limited Timeframe: The two-week period (February 1–16, 2024) may not fully capture the dynamics between public sentiment and stock prices under varied market conditions.

Data Source Bias: Reliance on Twitter excludes sentiment from other platforms, potentially limiting the breadth of public opinion.

Sentiment Analysis Challenges: Despite VADER lexicon customization, nuances like sarcasm or cultural context may reduce classification accuracy.

External Influences: The study does not consider macroeconomic, geopolitical, or industry-specific factors, complicating the isolation of sentiment- driven effects.

6.2 Future Scope of the Study

Extended Analysis: Incorporate a longer timeframe and data from multiple platforms like Facebook and Reddit to enhance generalizability.

Incorporating Macroeconomic Factors: Consider key elements like news sentiment and market competition to gain a well-rounded understanding of factors influencing stock prices**.**

Leveraging Advanced Models: Employ the latest machine learning and deep learning techniques to enhance prediction accuracy.

Industry-Specific Analysis: Extend the research to other sectors to determine if the findings are relevant beyond the fintech industry.

Real-Time Implementation: Create tools that merge sentiment analysis with live forecasts of stock prices enabling timely and informed decision- making.

7. CONCLUSION

This research points out the relationship between public opinion and investment strategy using Paytm as an example. The results show that while the public opinion is a posterior indicator of market activity is neither a cause nor a prediction; it is often the performance of the stock that affects the sentiment which is causal relationship.

The study looks into the topic of sentiment analysis in the context of finance in greater depth offering companies and investors with actionable measures to mitigate risk and to look at the direction of market dynamics. There are shortcomings such as the short time range, focus on Twitter, however, these hurdles can be overcome in subsequent research due to history data and more intricate techniques and more comprehensive approaches.

At the end, this investigation shows why social media is seen as an asset in evaluating investors' sentiment regarding a certain market, especially when this market goes under tremendous stress due to a crisis, regulatory intervention and the other reason which require quick and informed decisions from actors in this market.

BIBLIOGRAPHY

1. Divyansh, Koolwal. (2024). Integrating Twitter Sentiment with ML Models for Enhanced Stock Forecasting. International Journal for Research in Applied Science and Engineering Technology, 12(10):505- 518. doi: 10.22214/ijraset.2024.64561
2. S., Iniyan., J., ThangaKumar., P., Selvi, Rajendran. (2024). Twitter Scraping and Sentiment Analysis on Stock Price. 1-6. doi: 10.1109/adics58448.2024.10533556
3. Et, al., Shubham, Shah. (2023). Stock Prediction using GAN and Sentiment Analysis. International Journal on Recent and Innovation Trends in Computing and Communication, 11(9):2307-2316. doi: 10.17762/ijritcc.v11i9.9238
4. Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges.
5. Zhang, Y., & Wang, D. (2011). Twitter Sentiment Analysis: A Survey of Techniques.
6. Bollen, J., & Mao, H. (2011). Twitter mood as a stock market predictor. IEEE Computer, 44(10), 91–94.
7. Meera, Mehta., Shiv, Arora., Shikhar, Raj, Gupta., Arun, Jhulka. (2022). Social Listening Through Sentiment Analysis of Twitter Data: A Case Study of Paytm IPO. Socioeconomic challenges, 6(3):39-47. doi: 10.21272/sec.6(3).39-47.2022
8. Sánchez-Rada JF, Iglesias CA (2019) Social context in sentiment analysis: formal definition, overview of current trends and framework for comparison. Inf Fusion 52:344–356
9. Asur, S., Huberman, B.A.: Predicting the Future with Social Media. In: Proceedings of the ACM International Conference on Web Intelligence, pp. 492-499 (2010)
10. Jain PK, Pamula R, Srivastava G (2021) A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. Computer Sci Rev 41:100413
11. Farheen, Khanum., P, Sree, Lakshmi., Harsha, Vardhan, Reddy., K. (2024). Sentiment Analysis Using Natural Language Processing, Machine Learning and Deep Learning. 113-118. doi: 10.1109/i4c62240.2024.10748425
12. Snehal, Sarangi. (2024). Comprehensive Analysis of Hybrid Machine Learning Models using Optimization Techniques for Improving Twitter Sentiment. Panamerican Mathematical Journal, doi: 10.52783/pmj.v34.i3.1776
13. Himanshu, Pal., Bharat, Bhushan. (2024). Sentiment Analysis on Twitter Dataset using Voting Classifier. 1-6. doi: 10.1109/iceect61758.2024.10739316
14. https://www.hindustantimes.com/business/ paytm-stock-share-price-live-updates- february-1-2024-sensex-nifty-budget- 2024-101706757577104.html
15. Kokoy, Siti, Komariah., Carmadi, Machbub., Ary, Setijadi, Prihatmanto., Bong-Kee, Sin. (2016). A Study on Efficient Market Hypothesis to Predict Exchange Rate Trends Using Sentiment Analysis of Twitter Data. Journal of Korea Multimedia Society, 19(7):1107-1115. doi: 10.9717/KMMS.2016.19.7.1107