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**DEPARTMENT OF COMMERCE**

**Impact of YouTuber's Recommendation on Stock Market Performance: Are the YouTubers Really Influential?**

## Report Submitted By

Sathwik Kamath

In partial fulfilment of the award of the degree of

## M.Sc. Business Analytics

Under the Guidance of

Mr.Sanket Ledwani,

Assistant Professor (Guide)

Department of Commerce

Manipal Academy of Higher Education

**June 2024**

**DECLARATION**

I, Sathwik Kamath, declare that this project titled "Analysing Perspectives: A Content Analysis of YouTube Videos on Electronic Cigarettes from Nov 2022 to Nov 2023" is my own work and that all sources used have been acknowledged. This work has not been previously submitted for a degree or diploma in any university or institution.

I further declare that:

1. I have adhered to the academic standards and ethical guidelines for research.
2. All information in this document is true and reflects my research findings.

Signed,

Sathwik Kamath

Date: 8th June 2024

## **GUIDE CERTIFICATE**

This is to certify that **Mr. Sathwik Kamath, Roll Number 222626013**, a student of **M.Sc. Business Analytics** has successfully completed the project titled:

**"Testing the Credibility of the Stock Market Influencers: An Event Study on NIFTY50 & NIFTY Smallcap 50 Companies"**

under the guidance of **Mr. Sanket Ledwani**, Assistant Professor (Guide), Department of Commerce, Manipal Academy of Higher Education.

The project report submitted is a record of original work done by the student under the supervision of the guide and is submitted in partial fulfillment of the requirements for the degree of Master of Science in Business Analytics.

**Assistant Professor (Guide)**

**Department of Commerce**

**Manipal Academy of Higher Education**

**Date:**

**Place: Manipal**

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Thank you all for your support and assistance.

Sincerely,  
Sathwik Kamath

**Impact of YouTuber's Recommendation on Stock Market Performance: Are the YouTubers Really Influential?**

**Abstract**

This study investigates the accuracy and credibility of YouTube stock market influencers by examining whether their predicted returns align with actual market performance. Focusing on companies listed in the NIFTY50 and NIFTY Smallcap 50 indices, the analysis utilises the BERT model for advanced sentiment analysis of YouTube comments, assessing perceived sentiment and its correlation with stock prices. By employing an event study methodology, we measure abnormal returns (AR) and cumulative abnormal returns (CAR) to evaluate the accuracy of these influencers' predictions. The study is conducted within a fixed-effect model framework, aiming to determine the reliability of YouTubers' recommendations and whether they can be trusted for investment decisions. The findings offer crucial insights for investors, regulators, and market participants regarding the influence and trustworthiness of social media-driven stock market predictions.

1. **Introduction: 2 pages**

In the digital age, social media platforms have revolutionised how information is disseminated and consumed, with YouTube emerging as a powerful medium for influencing public opinion across various fields, including finance. YouTube influencers, particularly those focusing on stock market analysis and predictions, have gained significant followings, often shaping the investment decisions of their viewers. Through their content, these influencers offer stock recommendations and market insights that many small investors rely on when making investment choices. However, the crucial question is whether these influencers' predictions are accurate and trustworthy. This study explores this question by examining the extent to which YouTube stock market influencers can be relied upon for accurate financial advice, particularly in the context of companies listed in the NIFTY50 and NIFTY Smallcap 50 indices.

The increasing reliance on social media for financial information has drawn the attention of both researchers and market participants. Existing research has demonstrated that social media can profoundly impact stock market performance, with studies highlighting the correlation between online sentiment and stock prices. Platforms like Twitter have been extensively studied, showing that public sentiment expressed through tweets can influence market movements, particularly in developed economies. However, research focusing on YouTube as a source of stock market information, especially in emerging markets like India, remains limited. This study seeks to fill this gap by investigating the credibility of YouTube influencers who provide stock market predictions.

Previous studies have also shown that the impact of social media on financial markets can vary depending on the platform and the audience. While Twitter has been recognised for its ability to disseminate news quickly, leading to immediate market reactions, YouTube offers a more in-depth and visual medium where influencers can elaborate on their market analyses and predictions. The format and reach of YouTube content mean that these influencers can build strong relationships with their audiences, often positioning themselves as trusted sources of financial advice. However, the lack of regulation and the potential for biased or unverified information raises concerns about the reliability of these predictions.

Research on the accuracy of financial predictions made by social media influencers is still in its nascent stages. While numerous studies examine the general impact of social media on stock prices, there is a noticeable gap in understanding how specific influencers on platforms like YouTube affect investor behaviour and market outcomes. This study addresses this gap by focusing on the Indian stock market and evaluating whether the returns predicted by YouTube influencers align with actual market performance. Doing so aims to provide insights into whether these influencers can be trusted to make informed investment decisions.

The relevance of this research extends beyond academic inquiry, as it has significant implications for small investors who often lack the resources to conduct their own market analysis. These investors may turn to YouTube influencers for guidance, making it critical to assess whether such trust is well-placed. If these influencers' predictions are not grounded in solid financial analysis, there is a risk that followers could make poor investment choices, leading to financial losses. Therefore, evaluating the credibility of YouTube influencers is important for individual investors and maintaining the integrity of the market as a whole.

Moreover, the role of social media in shaping financial markets is becoming increasingly important, especially in emerging economies where traditional sources of financial information may not be as accessible or trusted. The Indian stock market, with its unique characteristics and growing influence, provides an ideal context for examining the interplay between social media influence and market performance. As more investors in India and other emerging markets turn to social media for investment advice, understanding the accuracy and reliability of such information becomes crucial.

In conclusion, this study seeks to determine whether YouTube stock market influencers can be trusted by evaluating the alignment between their predictions and actual market outcomes. By exploring this issue, the research contributes to the broader understanding of the influence of social media on financial decision-making and the potential risks involved in relying on digital influencers for investment advice. The findings of this study will offer valuable insights for investors, regulators, and market participants as they navigate the evolving landscape of social media-driven financial information.

1. **Research Methodology:2 to 3 Pages** 
   1. **Sample Selection**

In this study, we selected companies from the NIFTY50 and NIFTY Smallcap 50 indices to comprehensively analyse the Indian stock market. The NIFTY50 index consists of 50 large-cap companies known for their stable performance and significant market influence, while the NIFTY Smallcap 50 index includes 50 small-cap companies that typically exhibit higher volatility and growth potential. This dual approach allows us to examine how YouTube influencers affect companies with varying market capitalisations and risk profiles, providing a broad understanding of market dynamics.

One company from each sector within the NIFTY50 and NIFTY Smallcap 50 indices was selected based on the highest free-float market capitalisation to ensure a representative sample. Free-float market capitalisation reflects the market value of shares available for public trading, excluding those held by insiders. This selection criterion ensures that the chosen companies are significant players in their respective sectors and have a substantial number of shares available for public trading, which is crucial for assessing the impact of market influencers.

Table 1: Selected NIFTY50 Companies by Sector

| **Sector** | **Company** |
| --- | --- |
| Healthcare | Sun Pharmaceutical Inds. Ltd. |
| Automobile and Auto Components | Mahindra & Mahindra Ltd. |
| Construction | Larsen & Toubro Ltd. |
| Construction Materials | UltraTech Cement Ltd. |
| Consumer Durables | Titan Company Ltd. |
| Fast Moving Consumer Goods | I T C Ltd. |
| Financial Services | HDFC Bank Ltd. |
| Information Technology | Infosys Ltd. |
| Metals & Mining | Tata Steel Ltd. |
| Oil Gas & Consumable Fuels | Reliance Industries Ltd. |
| Power | NTPC Ltd. |
| Services | Adani Ports & Special Economic Zone Ltd. |
| Telecommunication | Bharti Airtel Ltd. |

Table 2: Selected NIFTY Small cap 50 Companies by Sector

| **Sector** | **Company** |
| --- | --- |
| Automobile and Auto Components | Exide Industries Ltd. |
| Capital Goods | Apar Industries Ltd. |
| Chemicals | Aarti Industries Ltd. |
| Construction | NCC Ltd. |
| Consumer Durables | Crompton Greaves Consumer Electricals Ltd. |
| Consumer Services | Indiamart Intermesh Ltd. |
| Fast Moving Consumer Goods | Radico Khaitan Ltd. |
| Financial Services | Multi Commodity Exchange of India Ltd. |
| Forest Materials | Century Textiles & Inds. Ltd. |
| Healthcare | Glenmark Pharmaceuticals Ltd. |
| Information Technology | Cyient Ltd. |
| Media Entertainment & Publication | PVR Inox Ltd. |
| Metals & Mining | National Aluminium Co. Ltd. |
| Oil Gas & Consumable Fuels | Gujarat State Petronet Ltd. |
| Power | CESC Ltd. |
| Services | Great Eastern Shipping Co. Ltd. |
| Telecommunication | HFCL Ltd. |
| Textiles | Raymond Ltd. |

These selections provide a balanced representation of the sectors within both indices. The analysis will focus on the most significant companies regarding market influence and share availability, ensuring a robust foundation for assessing the influence of YouTube stock market influencers.

* 1. **Data Source:**

The data for this study were collected from two primary sources: YouTube and the National Stock Exchange (NSE) website.

YouTube is the platform from which video content related to stock market analysis was collected. These videos, created by various influencers, contain predictions and analyses that retail investors widely consume. The videos were tailored to include those focusing specifically on stock forecasts, market analysis, and investment recommendations for the companies in the NIFTY50 and NIFTY Smallcap 50 indices. This data provides insights into the sentiment and predictions these influencers disseminate, which are then analysed to assess their impact on stock market performance.

The NSE website was used to obtain accurate and reliable financial data for the selected companies. This data includes stock prices, market capitalisations, and other relevant required financial metrics for evaluating the accuracy of the predictions made by YouTube influencers. By combining sentiment data from YouTube with financial data from the NSE, this study offers a detailed analysis of whether the predictions made by these influencers align with actual market outcomes.

* 1. **Sentiment Analysis: sentiment, Perceived sentiment**

In this project, we assessed the sentiment of YouTube stock market influencers to determine whether their predictions could be trusted. We used Python and the YouTube Data API to collect relevant video content, enabling us to gather video details based on specific search strings efficiently. These strings were designed to capture videos directly related to the companies in our study, such as “[Company Name] stock analysis,” “[Company Name] stock review,” and “[Company Name] forecast.” By employing these tailored search terms, we ensured that the videos selected were relevant to our analysis, targeting content likely to influence investor sentiment.

Once the data was collected, we applied several filtering criteria. Videos that were duplicates, off-topic, or not original were removed. The study focused on videos released between April 1, 2022, and March 31, 2024, to ensure our analysis reflected current market trends and excluded any unusual impacts caused by the COVID-19 pandemic. Additionally, to further refine the dataset, we selected only videos from channels with the highest subscriber counts, ensuring that the influencers under analysis had a strong following and were likely to impact investor decisions significantly. After filtering, we had a final dataset of 170 videos for NIFTY50 companies and 172 for NIFTY Smallcap 50 companies.

For sentiment analysis, we selected BERT (Bidirectional Encoder Representations from Transformers) over VADER (valence-aware dictionary and sentiment Reasoner) due to BERT's superior ability to handle long-form content, such as video transcripts. While VADER is effective for short texts and informal language, it is limited when processing longer, complex sentences. BERT, on the other hand, is designed to understand context and nuances in the text by using a deep learning architecture that reads the text in both directions. This made BERT an ideal choice for our project, as the transcripts from YouTube videos often contain detailed and nuanced stock market discussions.

In preparation for analysis, we translated all non-English transcripts to English using Python’s GoogleTranslator package. Afterwards, we fine-tuned the pre-trained BERT model to better suit our dataset, ensuring optimal performance for analysing stock market-related content. The BERT model was then applied to each video transcript, classifying the sentiment as positive, negative, or neutral and providing confidence scores for these classifications. These confidence scores were essential in assessing the reliability of the sentiment analysis, indicating how certain the model was in its predictions.

We extended our sentiment analysis beyond the influencers' statements by also considering the viewers’ reactions, as reflected in the video comments. This provided a more comprehensive picture of how their audience perceived the influencers' predictions.

**Perceived Sentiment**

For the analysis of viewer comments, we utilised the VADER sentiment model. VADER is particularly effective in analysing the informal and conversational language often found in YouTube comments, including emojis and slang. We extracted the comments from the selected videos, preprocessed them by cleaning irrelevant content, and translated non-English comments into English. VADER was then applied to evaluate the sentiment of these comments, providing scores for positive, negative, neutral, and compound sentiment.

The perceived sentiment derived from the VADER analysis helped us gauge whether the influencers' predictions resonated with their audience. By comparing the sentiment expressed in the videos to the viewers' reactions, we fully understood the influencers’ credibility. In particular, the average positive, negative, neutral, and compound sentiment scores for each video’s comments provided insights into whether viewers agreed with or trusted the predictions.

This dual approach of analysing the videos and their comments ensured that we could evaluate the influencers and their audience's perceived sentiments. By combining these two elements, we can better assess whether the influencers' predictions align with reality and whether investors can trust their advice.

* 1. **Event Study: CAR, AR, T-stat,**

We conducted an event study to analyse the impact of YouTube stock market influencers on the prices of NIFTY50 and NIFTY Smallcap 50 companies. This approach helps to isolate the effect of a particular event—in this case, the release of YouTube videos—on stock prices. The event study method allows us to observe how stock prices deviate from their expected returns within a specified event window. By focusing on abnormal returns (AR), which represent the difference between actual and expected returns, we can assess whether the influencers' predictions had a measurable effect on stock performance.

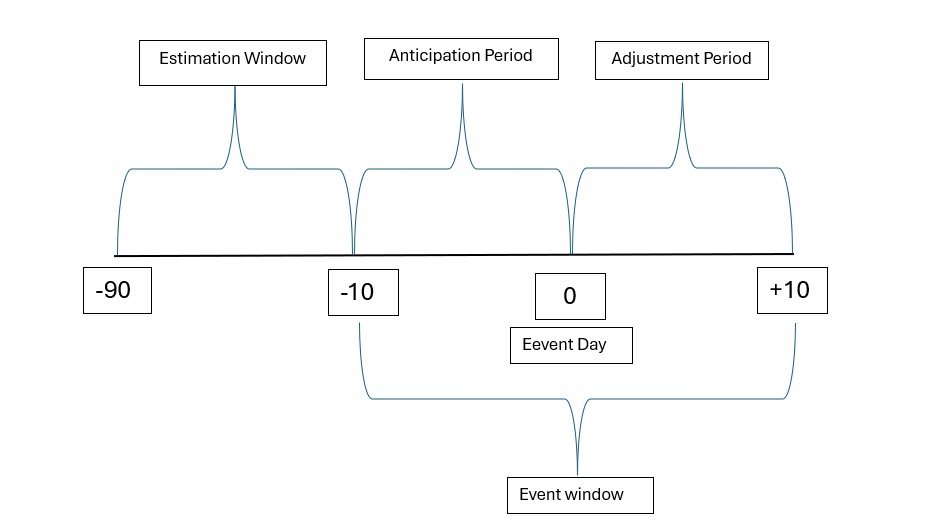


Figure 1

For this analysis, the event date is defined as the day the video was uploaded. However, if the video was released after 2:30 PM IST, the following trading day is considered the event date. This adjustment accounts for the stock market closing, as video releases late in the day are unlikely to influence trading on the same day. We defined three windows around the event: the estimation window (90 days prior to the event), the anticipation window (10 days before the event), and the adjustment window (10 days after the event). This event window helps capture both the immediate and delayed effects of the influencer’s video on stock prices. A visual representation of the event window is included in Figure 1.

The abnormal return (AR) for a given day is calculated using the formula:

where Rt is the actual return on the stock on the day, and E(Rt) is the expected return, typically estimated based on a historical period (the estimation window). The expected return is calculated as the mean return over the 90 days before the anticipation window begins. This helps isolate the stock’s normal performance, allowing us to focus on deviations triggered by the event.

To understand the cumulative impact over multiple days, we calculate the cumulative abnormal return (CAR). CAR is the sum of abnormal returns over a specified time window, such as CAR (2), CAR(5), and CAR(10), which represent cumulative abnormal returns over 2, 5, and 10 days, respectively, after the event. The formula for CAR is:

where t1​ and t2​ represent the start and end of the event window. This metric helps assess the overall effect of the influencer's recommendation on stock prices over some time rather than focusing on single-day changes.

To determine the significance of the abnormal returns, we calculate the t-statistic, which is crucial for understanding whether the deviations in stock prices are statistically significant. The t-statistic for AR is computed using the formula:

where σ is the standard deviation of returns in the estimation window. Similarly, the t-statistic for CAR is calculated as:

where n is the number of days in the event window. These t-statistics allow us to assess whether the abnormal returns observed are significant enough to conclude that the YouTube influencer's video impacted the stock price.

By implementing this event study, we can objectively evaluate whether the predictions of YouTube stock market influencers correlate with real stock market movements, providing insight into whether investors can trust their advice.

* 1. **Fixed Effect Model**

In this project, we utilised the fixed-effect model to evaluate whether YouTube stock market influencers' predictions align with actual stock performance and whether viewers acted on these predictions by purchasing shares. The fixed-effect model is a powerful statistical tool that helps control for unobserved factors specific to each channel and period, ensuring that our results focus solely on the relationship between influencers' activities and stock market behaviour. This approach is handy for panel data, where repeated observations of the same entities—such as YouTube channels or companies—are recorded over time. Using this model, we accounted for channel-specific characteristics and time-based effects, isolating the true impact of the influencers’ predictions on cumulative abnormal returns (CAR).

To ensure robust results, we used a method that adjusts the standard errors to account for any potential heteroskedasticity and autocorrelation in the data. This adjustment enhances the reliability of the estimates without focusing on the technicalities of the code used for this process.

Several key variables were included in the fixed-effect model to capture the influence of YouTube videos on stock performance. **log(V)** represents the logarithm of the views a video has received, reflecting the video’s reach and potential influence on viewers. **log(SC)** stands for the logarithm of the YouTube channel’s subscriber count, providing insight into the overall popularity and authority of the influencer. **AR**, or Abnormal Return, represents the difference between a stock’s actual return and its expected return, offering a direct measure of how the market reacts to the information shared in the videos.

The model also incorporates sentiment variables that reflect the emotions expressed in video comments. **APC** is the average perceived compound sentiment, summarizing the overall emotional tone (positive, negative, and neutral) in viewer comments. **APP** represents the average perceived positive sentiment, indicating the proportion of viewers who responded positively to the video. **APN**, or average perceived negative sentiment, captures how much negative sentiment is expressed, while **APNeu**, or average perceived neutral sentiment, reflects emotionally neutral comments.

Additionally, we created interaction terms from the BERT sentiment analysis to capture the relationship between influencer content and stock performance. **BPI (BERT Positive Interaction)**, **BNI (BERT Negative Interaction)**, and **BNeuI (BERT Neutral Interaction)** were constructed by adding a dummy variable for each BERT sentiment type (positive, negative, and neutral), which was then multiplied by the corresponding BERT confidence score. This allowed us to assess the influence of positive, negative, and neutral content in the videos on stock prices more precisely. These interaction terms enabled the model to capture complex relationships between influencer content and market reactions.

The model is specified as follows:

In this equation, the dependent variable CARit​ represents the cumulative abnormal returns for the company i at time t. This allows us to assess how much the stock prices deviate from their normal behaviour following the release of a YouTube video. The independent variables, including views, subscriber count, abnormal returns, and sentiment metrics, help us determine whether audience engagement and sentiment expressed in the video content significantly influence stock performance.

The terms αt and λt​ represent fixed effects specific to each YouTube channel and period, respectively. These fixed effects account for any unobservable factors that vary between channels or time but remain constant within them. By including these terms, we ensure that the model isolates the true relationship between influencer predictions and stock market reactions, independent of other external factors.

By applying this fixed effect model to both NIFTY50 and NIFTY Smallcap 50 companies, we could compare the influence of YouTube stock market influencers on large-cap and small-cap companies. This analysis provides valuable insights into whether influencer predictions can significantly affect investor behaviour and stock market outcomes, highlighting the potential credibility and market impact of these social media influencers.

1. **Results And findings: 5 Pages**
   1. **Summary Results**

Table 3: Summary of Returns on Event Study Results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Positive | | Negative | |
| Video Sentiment | Significant | Insignificant | Significant | Insignificant |
| Positive | Significantly Correct | Insignificant Suggestion Correct | Significantly Wrong | Insignificant Suggestion Wrong |
| Negative | Significantly Wrong | Insignificant Suggestion Wrong | Significantly Correct | Insignificant Suggestion Correct |
| Neutral | Failed to Predict | Irrelevant Videos | Failed to Predict | Irrelevant Videos |

Table 4: Summary of Abnormal Returns on the event day.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Abnormal Return** | | | | | | | | | | |
| ***Company Name*** | ***S C*** | ***S W*** | ***I S C*** | ***I S W*** | ***I V*** | ***F P*** | ***Total*** | ***T S*** | ***P C*** | ***N C*** |
| **Exide Industries Ltd** | 1 | 0 | 4 | 3 | 4 | 2 | 14 | 1 | 1 | 0 |
| **Apar Industries Ltd** | 0 | 0 | 1 | 1 | 3 | 2 | 7 | 0 | 0 | 0 |
| **Aarti Industries Ltd** | 0 | 0 | 0 | 0 | 7 | 2 | 9 | 0 | 0 | 0 |
| **N C C Ltd** | 1 | 0 | 1 | 0 | 6 | 1 | 9 | 1 | 1 | 0 |
| **Crompton Greaves Consumer Electricals Ltd** | 3 | 0 | 4 | 1 | 6 | 2 | 16 | 3 | 2 | 1 |
| **Indiamart Intermesh Ltd** | 1 | 0 | 1 | 0 | 2 | 2 | 6 | 1 | 1 | 0 |
| **Radico Khaitan Ltd** | 0 | 1 | 1 | 5 | 0 | 0 | 7 | 1 | 0 | 0 |
| **Multi Commodity Exchange of India Ltd** | 0 | 0 | 0 | 2 | 4 | 0 | 6 | 0 | 0 | 0 |
| **Century Textiles & Inds. Ltd** | 0 | 0 | 1 | 3 | 3 | 2 | 9 | 0 | 0 | 0 |
| **Glenmark Pharmaceuticals Ltd** | 4 | 3 | 3 | 1 | 3 | 11 | 25 | 7 | 4 | 0 |
| **Cyient Ltd** | 0 | 1 | 1 | 1 | 0 | 1 | 4 | 1 | 0 | 0 |
| **P V R Inox Ltd** | 2 | 1 | 2 | 6 | 4 | 2 | 17 | 3 | 2 | 0 |
| **National Aluminium Co. Ltd** | 3 | 0 | 1 | 0 | 1 | 1 | 6 | 3 | 3 | 0 |
| **Gujarat State Petronet Ltd** | 0 | 1 | 0 | 0 | 2 | 2 | 5 | 1 | 0 | 0 |
| **C E S C Ltd** | 0 | 0 | 1 | 0 | 2 | 0 | 3 | 0 | 0 | 0 |
| **Great Eastern Shipping Co. Ltd** | 1 | 0 | 3 | 0 | 6 | 2 | 12 | 1 | 1 | 0 |
| **H F C L Ltd** | 0 | 0 | 1 | 0 | 3 | 3 | 7 | 0 | 0 | 0 |
| **Raymond Ltd** | 3 | 0 | 1 | 1 | 1 | 4 | 10 | 3 | 3 | 0 |
| **Larsen & Toubro Ltd** | 1 | 0 | 3 | 1 | 2 | 3 | 10 | 1 | 1 | 0 |
| **Adani Ports & Special Economic Zone Ltd** | 1 | 1 | 1 | 1 | 5 | 0 | 9 | 2 | 1 | 0 |
| **Bharti Airtel Ltd** | 2 | 1 | 2 | 3 | 11 | 3 | 22 | 3 | 2 | 0 |
| **Sun Pharmaceutical Inds. Ltd** | 3 | 1 | 2 | 0 | 0 | 0 | 6 | 4 | 3 | 0 |
| **Mahindra & Mahindra Ltd** | 0 | 0 | 1 | 0 | 4 | 1 | 6 | 0 | 0 | 0 |
| **UltraTech Cement Ltd** | 4 | 0 | 5 | 3 | 8 | 2 | 22 | 4 | 4 | 0 |
| **Titan Company Ltd** | 0 | 0 | 1 | 1 | 3 | 2 | 7 | 0 | 0 | 0 |
| **HDFC Bank Ltd** | 0 | 0 | 2 | 1 | 10 | 7 | 20 | 0 | 0 | 0 |
| **ITC Ltd** | 0 | 0 | 2 | 2 | 3 | 1 | 8 | 0 | 0 | 0 |
| **Infosys Ltd** | 0 | 0 | 1 | 0 | 3 | 2 | 6 | 0 | 0 | 0 |
| **Tata Steel Ltd** | 0 | 0 | 4 | 1 | 11 | 0 | 16 | 0 | 0 | 0 |
| **Reliance Industries Ltd** | 4 | 0 | 4 | 1 | 15 | 2 | 26 | 4 | 4 | 0 |
| **NTPC Ltd** | 1 | 1 | 2 | 1 | 4 | 3 | 12 | 2 | 1 | 0 |
| **Total** | 35 | 11 | 56 | 39 | 136 | 65 | 342 | 46 | 34 | 1 |
| ***Percentage*** | *10.23* | *3.22* | *16.37* | *11.40* | *39.77* | *19.01* | *100* | *13.45* | *9.94* | *0.29* |

NOTE: S C: Significantly Correct, S W: Significantly Wrong, I S C: Insignificant Suggestion Correct, I S W: Insignificant Suggestion Wrong, I V: Irrelevant Videos, F P: Failed to Predict, T S: Total Significant, P C: Positive Correct, N C: Negative Correct.

The analysis of abnormal returns and cumulative abnormal returns (CAR) reveals several important patterns. For the abnormal returns, a total of 342 instances were recorded, with 35 cases being classified as "Significantly Correct" (S C), representing 10.23% of the total. On the other hand, 11 cases were "Significantly Wrong" (S W), amounting to 3.22%. Additionally, 56 cases were labelled as "Insignificant Suggestion Correct" (I S C), representing 16.37%, while 39 were categorised as "Insignificant Suggestion Wrong" (I S W), accounting for 11.40%. The majority of instances fell under "Irrelevant Videos" (I V) with 136 cases, representing 39.77% of the total, followed by "Failed to Predict" (F P) with 65 cases, or 19.01%. The overall significant cases (T S) totalled 46, accounting for 13.45% of the total, with 34 cases of "Positive Correct" (P C), and only 1 case of "Negative Correct" (N C).

Table 5 : Summary of Cumulative Abnormal Returns (CAR 2) for Two days after event observation.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **CAR(2)** | | | | | | | | | | |
| ***Company Name*** | ***S C*** | ***S W*** | ***I S C*** | ***I S W*** | ***I V*** | ***F P*** | ***Total*** | ***T S*** | ***P C*** | ***N C*** |
| **Exide Industries Ltd** | 0 | 0 | 4 | 4 | 6 | 0 | 14 | 0 | 0 | 0 |
| **Apar Industries Ltd** | 0 | 0 | 0 | 2 | 5 | 0 | 7 | 0 | 0 | 0 |
| **Aarti Industries Ltd** | 0 | 0 | 0 | 0 | 7 | 2 | 9 | 0 | 0 | 0 |
| **N C C Ltd** | 1 | 0 | 0 | 1 | 7 | 0 | 9 | 1 | 1 | 0 |
| **Crompton Greaves Consumer Electricals Ltd** | 1 | 0 | 4 | 3 | 8 | 0 | 16 | 1 | 0 | 1 |
| **Indiamart Intermesh Ltd** | 0 | 0 | 2 | 0 | 4 | 0 | 6 | 0 | 0 | 0 |
| **Radico Khaitan Ltd** | 0 | 0 | 2 | 5 | 0 | 0 | 7 | 0 | 0 | 0 |
| **Multi Commodity Exchange of India Ltd** | 0 | 0 | 2 | 0 | 4 | 0 | 6 | 0 | 0 | 0 |
| **Century Textiles & Inds. Ltd** | 0 | 0 | 3 | 1 | 5 | 0 | 9 | 0 | 0 | 0 |
| **Glenmark Pharmaceuticals Ltd** | 0 | 3 | 6 | 2 | 5 | 9 | 25 | 3 | 0 | 0 |
| **Cyient Ltd** | 0 | 0 | 0 | 3 | 1 | 0 | 4 | 0 | 0 | 0 |
| **P V R Inox Ltd** | 0 | 1 | 6 | 4 | 6 | 0 | 17 | 1 | 0 | 0 |
| **National Aluminium Co. Ltd** | 1 | 0 | 3 | 0 | 2 | 0 | 6 | 1 | 1 | 0 |
| **Gujarat State Petronet Ltd** | 0 | 0 | 0 | 1 | 4 | 0 | 5 | 0 | 0 | 0 |
| **C E S C Ltd** | 0 | 0 | 1 | 0 | 2 | 0 | 3 | 0 | 0 | 0 |
| **Great Eastern Shipping Co. Ltd** | 0 | 0 | 2 | 2 | 8 | 0 | 12 | 0 | 0 | 0 |
| **H F C L Ltd** | 0 | 0 | 1 | 0 | 6 | 0 | 7 | 0 | 0 | 0 |
| **Raymond Ltd** | 0 | 0 | 3 | 2 | 5 | 0 | 10 | 0 | 0 | 0 |
| **Larsen & Toubro Ltd** | 0 | 0 | 4 | 1 | 3 | 2 | 10 | 0 | 0 | 0 |
| **Adani Ports & Special Economic Zone Ltd** | 1 | 2 | 0 | 1 | 5 | 0 | 9 | 3 | 1 | 0 |
| **Bharti Airtel Ltd** | 0 | 0 | 1 | 7 | 14 | 0 | 22 | 0 | 0 | 0 |
| **Sun Pharmaceutical Inds. Ltd** | 0 | 0 | 4 | 2 | 0 | 0 | 6 | 0 | 0 | 0 |
| **Mahindra & Mahindra Ltd** | 0 | 0 | 1 | 0 | 5 | 0 | 6 | 0 | 0 | 0 |
| **UltraTech Cement Ltd** | 0 | 0 | 8 | 4 | 10 | 0 | 22 | 0 | 0 | 0 |
| **Titan Company Ltd** | 0 | 0 | 0 | 2 | 5 | 0 | 7 | 0 | 0 | 0 |
| **HDFC Bank Ltd** | 0 | 1 | 1 | 1 | 15 | 2 | 20 | 1 | 0 | 0 |
| **ITC Ltd** | 0 | 0 | 3 | 1 | 3 | 1 | 8 | 0 | 0 | 0 |
| **Infosys Ltd** | 0 | 0 | 1 | 0 | 3 | 2 | 6 | 0 | 0 | 0 |
| **Tata Steel Ltd** | 0 | 0 | 4 | 1 | 11 | 0 | 16 | 0 | 0 | 0 |
| **Reliance Industries Ltd** | 2 | 1 | 4 | 2 | 17 | 0 | 26 | 3 | 2 | 0 |
| **NTPC Ltd** | 0 | 0 | 2 | 3 | 6 | 1 | 12 | 0 | 0 | 0 |
| **Total** | 6 | 8 | 72 | 55 | 182 | 19 | 342 | 14 | 5 | 1 |
| ***Percentage*** | *1.75* | *2.34* | *21.05* | *16.08* | *53.22* | *5.56* | *100* | *4.09* | *1.46* | *0.29* |

NOTE: S C: Significantly Correct, S W: Significantly Wrong, I S C: Insignificant Suggestion Correct, I S W: Insignificant Suggestion Wrong, I V: Irrelevant Videos, F P: Failed to Predict, T S: Total Significant, P C: Positive Correct, N C: Negative Correct.

For the CAR(2) analysis, similar trends emerge. Out of the 342 cases, six were categorised as "Significantly Correct" (S C), accounting for only 1.75%, while 8 cases were marked as "Significantly Wrong" (S W), representing 2.34%. A significant number of instances, 72 (21.05%), were "Insignificant Suggestion Correct" (I S C), whereas 55 cases (16.08%) fell under "Insignificant Suggestion Wrong" (I S W). Again, the majority of instances, 182 (53.22%), were categorised as "Irrelevant Videos" (I V), followed by 19 cases (5.56%) of "Failed to Predict" (F P). The total significant cases (T S) for CAR(2) amounted to 14, accounting for 4.09%, with 5 cases of "Positive Correct" (P C) and 1 case of "Negative Correct" (N C).

These results highlight that most video sentiments tend to either be irrelevant or fail to predict stock market movements effectively, with a relatively small percentage of cases being correctly predicted or significantly impacting abnormal or cumulative abnormal returns.

* 1. **Model Results**

This analysis evaluates the accuracy of YouTube influencers' predictions on stock price movements for companies in the NIFTY50 and NIFTY Small Cap 50 indices. By using a fixed-effect model, the study examines the alignment between influencers' recommendations and actual stock performance, focusing on how sentiment expressed in YouTube videos, as well as viewers' reactions, correlates with cumulative abnormal returns (CAR). The model measures these returns over three periods: CAR 2 (short-term), CAR 5 (medium-term), and CAR 10 (long-term). The primary goal is to assess how well influencers can predict stock prices, considering the video sentiment (using BERT) and audience sentiment (using VADER) from YouTube comments.

Table 6 : Fixed Effect model Result for NIFTY50

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **NIFTY50** | | | | | | |
| **Variables** | **CAR (2)** | | **CAR (5)** | | **CAR (10)** | |
| **Model 1** | **Model 2** | **Model 1** | **Model 2** | **Model 1** | **Model 2** |
| log(V) | -0.0028 | 0.000004 | -0.0018 | -0.0036 | -0.0051\*\* | -0.0029 |
| (-0.7261) | (0.0020) | (-0.8425) | (-1.3050) | (-2.0914) | (-0.7649) |
| log (SC) | -0.1067 | -0.1062 | -0.0998 | -0.131 | -0.1004 | -0.0952 |
| (-0.7260) | (-1.3777) | (-1.4327) | (-1.2250) | (-0.9435) | (-0.6988) |
| AR | 1.2167\*\*\* | 1.0857\*\*\* | 1.0813\*\*\* | 1.0900\*\*\* | 1.1124\*\*\* | 1.1915\*\*\* |
| (9.6662) | (19.1520) | (18.8881) | (12.9617) | (14.3286) | (9.6439) |
| BPI | 0.0757\* | 0.0420\* | 0.0372 | 0.0748\*\* | 0.0635 | 0.0843\* |
| (1.8294) | (1.7561) | (1.4496) | (1.9786) | (1.5272) | (1.8199) |
| BNI | -0.0386 | -0.0266 | -0.016 | -0.0326 | -0.0143 | -0.0546 |
| (-0.8461) | (-0.9812) | (-0.5266) | (-0.7870) | (-0.2932) | (-1.1792) |
| BNeuI | 0.0885\*\* | 0.0494\*\* | 0.0433\* | 0.0854\*\* | 0.0724\* | 0.0957\* |
| (1.9934) | (2.0136) | (1.6730) | (2.1233) | (1.7307) | (1.9408) |
| APC |  | -0.0426\*\*\* |  | -0.0361\* |  | -0.0415 |
|  | (-4.0735) |  | (-1.7791) |  | (-1.2977) |
| APP |  | 0.0418\*\* |  | 0.02 |  | 0.0011 |
|  | (2.5135) |  | (0.7580) |  | (0.0254) |
| APN |  | -0.1097\*\*\* |  | -0.1250\*\*\* |  | -0.0994 |
|  | (-3.4410) |  | (-2.7319) |  | (-1.3873) |
| APNeu |  | 0.0019 |  | 0.0007 |  | 0.0238\*\* |
|  | (0.3682) |  | (0.0893) |  | 2.0000) |
| Observations | 170 | 170 | 170 | 170 | 170 | 170 |
| R2 | 0.4048 | 0.6596 | 0.6437 | 0.492 | 0.4819 | 0.4352 |
| Adjusted R2 | 0.2017 | 0.491 | 0.5222 | 0.2402 | 0.3051 | 0.1552 |
| Note: | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | | |

**NIFTY50 Results**

In the NIFTY50 analysis, the abnormal returns (AR) are highly significant across all periods, indicating that YouTube influencers tend to accurately predict stock price movements for large-cap companies. The positive sentiment (BPI) expressed by influencers is particularly significant in the short term (CAR 2) but grows even stronger when perceived sentiment variables are introduced, highlighting that the audience’s perception of these videos contributes significantly to the prediction accuracy. This suggests that the combination of influencer content and audience reaction enhances the ability to predict price movements in the short term.

Neutral sentiment becomes more significant over longer periods, especially in CAR 10. This shows that even videos that seem neutral can still predict stock price movements when combined with perceived audience sentiment. Furthermore, the perceived negative sentiment from the audience is significant in the shorter periods (CAR 2 and CAR 5), supporting the idea that negative reactions from viewers often lead to correct predictions of price declines. This is consistent with the market overreaction hypothesis, which posits that negative sentiment has a more lasting impact on prices than positive sentiment.

Comparing Model 1 and Model 2, adding perceived sentiment variables in Model 2 improves the model’s explanatory power, reflected in a higher R-squared value. This demonstrates that perceived sentiment contributes to better prediction accuracy. However, the overall R-squared values, while respectable (e.g., 0.6596 for CAR 2 in Model 2), suggest that other external factors influence stock price movements that are not captured by influencer predictions alone.

Table 7 : Fixed Effect Model Result for NIFTY 50 Small Cap

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **NIFTY Small Cap 50** | | | | | | |
| **Variables** | **CAR (2)** | | **CAR (5)** | | **CAR (10)** | |
| **Model 1** | **Model 2** | **Model 1** | **Model 2** | **Model 1** | **Model 2** |
| log(V) | 0.0024 | 0.0019 | -0.0001 | 0.0003 | 0.0018 | 0.0019 |
| (0.5738) | (0.6980) | (-0.0303) | (0.0760) | (0.4977) | (0.3835) |
| log (SC) | -0.1087 | -0.1392 | -0.2249 | 0.3252 | 0.2445 | 0.054 |
| (-0.3371) | (-0.7561) | (-0.8893) | (1.3751) | (0.6888) | (0.1531) |
| AR | 0.6725\*\*\* | 0.9624\*\*\* | 0.9877\*\*\* | 0.7060\*\*\* | 0.7051\*\*\* | 0.6372\*\*\* |
| (4.2665) | (12.4442) | (12.7378) | (8.1723) | (7.0671) | (4.7088) |
| BPI | 0.0845 | 0.0462 | 0.0605 | 0.0742 | 0.1243\*\*\* | 0.0552 |
| (1.1442) | (1.2605) | (1.4954) | (1.5088) | (2.9128) | (0.7800) |
| BNI | -0.1953 | -0.1493\* | -0.1736\*\* | -0.2106\* | -0.2870\*\*\* | -0.0991 |
| (-1.3749) | (-1.8361) | (-2.2221) | (-1.7485) | (-2.8022) | (-0.7130) |
| BNeuI | 0.0736 | 0.0346 | 0.0508 | 0.0707 | 0.1191\*\*\* | 0.0404 |
| (0.9650) | (0.9287) | (1.2645) | (1.4827) | (2.7625) | (0.5688) |
| APC |  | -0.0370\*\* |  | -0.0202 |  | 0.0261 |
|  | (-2.0235) |  | (-1.0458) |  | (0.7689) |
| APP |  | 0.0195 |  | 0.0467\*\* |  | -0.0454 |
|  | (1.0677) |  | (2.1044) |  | (-1.5000) |
| APN |  | -0.0229 |  | -0.0657 |  | -0.053 |
|  | (-0.8008) |  | (-1.3686) |  | (-0.7262) |
| APNeu |  | -0.0094 |  | 0.0128 |  | 0.0114 |
|  | (-0.9318) |  | (1.4602) |  | (0.8215) |
| Observations | 172 | 172 | 172 | 172 | 172 | 172 |
| R2 | 0.1754 | 0.6246 | 0.6113 | 0.2768 | 0.2963 | 0.1986 |
| Adjusted R2 | -0.0931 | 0.4467 | 0.4847 | -0.0661 | 0.0671 | -0.1814 |
| Note: | \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 | | | | | |

**NIFTY Small Cap 50 Results**

For NIFTY Small Cap 50 companies, the AR variable remains significant across all periods, indicating that YouTube influencers also have predictive power for small-cap stocks, but primarily in the short term. The model's explanatory power, measured by R-squared, is highest for CAR 2 (0.6246 in Model 2) but decreases significantly for longer periods (CAR 5 and CAR 10). This indicates that influencer predictions for small-cap stocks tend to lose relevance over time, and their accuracy diminishes as we move beyond short-term predictions.

Positive sentiment (BPI) predictions are significant over longer periods for small-cap stocks, showing that optimistic influencer predictions can align with long-term stock performance. However, negative sentiment (BNI) becomes more significant in the medium term (CAR 5 and CAR 10), suggesting that negative predictions, though delayed, are often correct for small-cap stocks. This pattern reflects the higher sensitivity of small-cap stocks to negative shocks, but these predictions are more transient and less persistent than those for larger companies.

The adjusted R-squared values for small-cap companies drop significantly, even becoming negative for CAR 5 and CAR 10 in Model 2, indicating a loss of model fit as time passes. This decline suggests that perceived sentiment remains significant only for short periods and becomes less predictive over time for smaller companies.

In conclusion, YouTube influencers' predictions are generally more accurate for NIFTY50 companies, particularly in the short term. The addition of perceived audience sentiment improves prediction accuracy for both indices, but its influence wanes over time for small-cap stocks.

In conclusion, the results from the fixed effects model and event study highlight the limited influence of YouTube stock market influencers on abnormal returns and cumulative abnormal returns. The fixed effects model indicated a significant relationship between sentiment metrics and stock performance, yet the majority of instances fell into categories such as "Irrelevant Videos" and "Failed to Predict," with only a small percentage classified as "Significantly Correct." The event study results further reinforced this observation, showing that only a fraction of cases resulted in significant predictive outcomes, emphasising the need for investors to approach social media sentiments with caution when making investment decisions.

1. **Discussion: 1 page**

The findings from the study on the impact of YouTube influencers' recommendations on stock market performance provide valuable insights into the complex interplay between social media sentiment and market behaviour. Interpretation of Results reveals that while YouTube influencers can somewhat predict stock price movements, their influence appears to be limited primarily to short-term gains, particularly for larger companies in the NIFTY50 index. The results of the fixed-effect model indicated a significant relationship between influencer sentiment and stock performance. Still, the prevalence of irrelevant videos and failed predictions suggests that many influencer predictions lack the depth and reliability needed for informed investment decisions.

Comparison with Previous Research aligns with studies that have indicated the impact of social media sentiment on market movements, particularly in platforms like Twitter. However, the findings of this study highlight a unique challenge in YouTube, where video content is often less timely and can reflect a delayed market response. Unlike platforms that facilitate rapid news dissemination, YouTube’s longer-form content may dilute the immediacy of its influence, reinforcing the need for a cautious approach to interpreting influencer recommendations.

The implications of this research are particularly relevant for retail investors who increasingly rely on social media for financial advice. YouTube influencers' significant yet limited predictive power calls for heightened scrutiny of their recommendations. Investors should consider the sentiment expressed by influencers and critically evaluate the content's relevance and the influencer’s track record. Furthermore, this study is a cautionary tale about the potential risks associated with blindly following influencer advice.

Limitations of the study include the focus on specific indices, which may not fully represent the entire stock market landscape. The analysis predominantly examined larger companies and their influencers, potentially overlooking the dynamics at play in smaller firms and various market conditions. Additionally, while robust, the sentiment analysis methods employed may not capture the full spectrum of audience reactions, particularly nuanced feelings expressed in comments that can differ from the sentiment in the video itself.

Future research could explore the influence of YouTube stock market content across different markets and indices, including the effects of various types of influencer content (e.g., educational versus promotional). Investigating how influencer credibility and follower engagement impact stock performance would also enhance understanding of this emerging field. Furthermore, integrating more advanced machine learning techniques for sentiment analysis may yield deeper insights into audience perceptions and their potential effects on market behavior.

In conclusion, while YouTube influencers have the potential to affect stock price movements, their predictive accuracy is variable, particularly over longer periods. This study underscores the importance of critical evaluation of influencer recommendations in the context of investment decisions, highlighting a growing need for further research into the reliability and impact of social media sentiment in financial markets.

1. **Conclusion: not more than a Page**

This study explored the influence of YouTube influencers on stock market performance, specifically focusing on their ability to predict stock price movements in the NIFTY50 and NIFTY Small Cap 50 indices. The research employed a fixed-effects model and event study methodology, incorporating sentiment analysis of YouTube videos and audience comments to assess the accuracy of influencer predictions. The findings indicate that while YouTube influencers can have a short-term impact on stock prices, particularly for larger companies, the overall predictive accuracy of their recommendations is limited.

The results demonstrate that a significant proportion of influencer predictions fall into categories such as "Irrelevant Videos" and "Failed to Predict," highlighting retail investors' challenges when relying on social media for investment advice. Despite the potential for influencers to drive short-term market movements, particularly through positive sentiment, the study reveals that many predictions lack the depth and reliability necessary for informed decision-making.

Moreover, the research contributes to the growing literature examining the intersection of social media and financial markets. It underscores the need for investors to approach influencer recommendations cautiously and critically evaluate the presented content. While positive sentiments can yield favourable short-term outcomes, the longer-term implications of such predictions remain uncertain.

In conclusion, this study emphasizes the importance of understanding the limitations of social media's influence on stock prices. It serves as a reminder that while YouTube influencers can shape market perceptions, their predictions should not be taken at face value. As social media continues to evolve, further research is needed to delve deeper into influencer content's credibility, audience engagement dynamics, and the broader implications for market behaviour. Ultimately, this research highlights the need for a balanced approach to utilising influencer insights in investment strategies, ensuring that investors remain well-informed and prudent in their decision-making processes.

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