Sentiment-Driven Market Dynamics: Evidence from Google Trends and Indian Stock Indices

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ABSTRACT

This study investigates the intersection of digital behavior and financial market activity by employing Google Trends data as a non-traditional, data-driven indicator of investor sentiment in the Indian context. Recognizing that investor psychology often drives market prices beyond fundamental values, the research explores whether web search query data can effectively capture and reflect investor sentiment and its influence on Nifty 50 index returns. Using the Google Sentiment Index (GSI) as a proxy for investor mood, the study employs quantile regression and Vector Autoregression (VAR) models to analyze the dynamic relationship between sentiment and market performance across varying return distributions. The quantile regression results indicate that the relationship between GSI and Nifty returns is asymmetric and non-linear with a significant negative effect during bearish conditions and a positive effect during bullish phases. This pattern highlights that sentiment exerts stronger short-term influence in extreme market conditions. The VAR analysis indicates a bidirectional feedback relationship between sentiment and returns; however, the predictive power of returns on sentiment is more pronounced, suggesting that investor sentiment is largely reactive to past market performance rather than predictive of future movements. Variance decomposition further confirms that daily market fluctuations are primarily self-driven, with sentiment playing a minimal role in explaining short-term return variance. The findings underscore that while sentiment derived from online behavior offers valuable behavioral insights, it serves as a weak predictor of daily returns and is more useful for identifying broader market trends and risk dynamics. By integrating behavioral finance with big data analytics, this research demonstrates the potential of Google search activity as a real-time tool for monitoring investor psychology, enhancing risk management, and informing strategic investment decisions in the Indian financial markets.

KEYWORDS

Behavioral Finance, Google Trends, Google Sentiment Index (GSI), Indian Stock Market, Investor Sentiment, Quantile Regression, Vector Autoregression (VAR)

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INTRODUCTION

In the evolving landscape of financial research, there has been a growing recognition of the limitations of traditional economic theories in explaining real-world market behavior. Classical finance models often assume that investors are fully rational and that markets are efficient. However, numerous instances of market overreactions, bubbles and crashes have challenged these assumptions, paving the way for the rise of behavioral finance as a complementary framework (Barberis & Thaler, 2003). Behavioral finance posits that psychological factors and cognitive biases significantly influence investor decisions, often leading to irrational market outcomes.

One such behavioral factor that has received increasing attention is investor sentiment, the overall attitude of investors toward a particular market or asset. Investor sentiment can be driven by various elements, including media coverage, economic news and social signals. This sentiment, especially when aggregated, have the potential to influence market prices, trading volumes, and volatility, even in the absence of fundamental information (Baker & Wurgler, 2007). While investor sentiment has long been considered an abstract concept, the digital age has introduced innovative methods to quantify and analyze it more objectively.

Among these new tools, Google trends has emerged as a powerful proxy for capturing public interest and investor attention. The Search Volume Index (SVI) provided by Google aggregates the frequency of specific search terms over time, reflecting what people are thinking about or concerned with at any given moment. Da, Engelberg, and Gao (2011) demonstrated that increased search activity on financial terms was associated with higher trading volumes and temporary stock price movements in the U.S. market. Similarly, Preis, Moat, and Stanley (2013) observed that search query volumes could serve as leading indicators of financial market trends.

Building on this growing body of literature in the context of the Indian stock market, the current study aims to examine the degree to which search query data obtained through Google trends can be utilized as a direct proxy for investor mood. The surge in digital engagement over years is also mirrored in the behavior of retail investors, who increasingly turn to search engines to gather market information, understand financial instruments and make investment decisions (Kumar & Garg, 2019). Understanding whether this online search behavior can effectively reflect market sentiment and, in turn, predict or explain stock market returns is crucial for multiple stakeholders. For investors, it offers a new dimension of sentiment analysis that can enhance trading strategies. For policymakers and regulators, it provides insights into market psychology and the potential risks of herd behavior. For researchers, it opens avenues for integrating big data tools with behavioral and empirical finance (Tetlock, 2007).

This study, therefore, aims to evaluate whether Google search volumes related to financial keywords are significantly associated with the performance of Indian stock indices. By combining behavioral finance concepts with data-driven methods, this research contributes to both theory and practice, highlighting how digital traces of investor attention can help bridge the gap between psychology and market behavior in an emerging economy.

LITERATURE REVIEW

Recent developments in financial research have underscored the limitations of traditional economic theories in explaining actual market behavior. Classical finance models often assume fully rational investors and efficient markets. Traditional finance, grounded in the principles of rational behavior and efficient markets, has served as the foundation of financial theory for decades. Markowitz's (1952) Modern Portfolio Theory introduced key concepts like diversification and the efficient frontier, shaping how portfolios are constructed. This was further developed by

Sharpe (1964) and Lintner (1965) through the Capital Asset Pricing Model (CAPM), which links expected returns to systematic risk. Fama's (1970) Efficient Market Hypothesis (EMH) built on these ideas, arguing that asset prices fully reflect all available information, making it difficult for investors to consistently outperform the market. Together, these theories formed the core of traditional finance, emphasizing rational decision-making and market efficiency, and provided a mathematical framework for understanding asset pricing, risk and investor behavior.

However, the inability of traditional models to explain certain market anomalies and investor behaviors led to the rise of behavioral finance. Influenced by the psychological research of Kahneman and Tversky (1979), this field integrates cognitive and emotional factors into financial decision-making. Behavioral finance highlights how biases, heuristics, and social influences can cause deviations from rationality, offering insights into phenomena that classical theories often fail to account for.

Investor sentiment, defined as beliefs not fully supported by fundamentals (Baker & Wurgler, 2007), plays a key role in behavioral finance. Unlike traditional finance, sentiment-based research explains anomalies in asset pricing and investor actions, especially for speculative stocks (Baker & Wurgler, 2006). Various sentiment measures surveys, market indicators like the VIX (Bandopadhyaya & Jones, 2008), media tone (Tetlock, 2007), and digital data from social media and Google Trends (Bollen et al., 2011; Li et al., 2014) have evolved, with recent approaches integrating machine learning for improved prediction (Ren et al., 2019). However, the absence of a universal sentiment metric and disagreement over its structure (Raissi & Missaoui, 2015; P.H. & Rishad, 2020) remain key challenges. Despite these limitations, sentiment analysis enriches financial modeling and market forecasting by offering a nuanced perspective beyond rational behavior assumptions.

More recently, the emergence of big data and advanced analytics has transformed financial research. Tools like Google Trends, which track search query volumes, have become powerful indicators of public interest and sentiment. These web-based data sources offer timely, real-world insights especially useful when traditional datasets are slow, noisy, or incomplete. In finance, they enable new methods of assessing investor attention, forecasting market movements, and understanding how information spreads across markets.

Behavioral finance research further strengthens the role of investor sentiment as a core state variable that complements and challenges traditional asset-pricing frameworks. Recent systematic reviews show that sentiment is central for explaining short-run return–sentiment linkages, particularly around crises and in emerging and frontier markets where information frictions are pronounced (Prasad et al., 2022; Luong et al., 2024; Kamath et al., 2024). These studies highlight that assumptions of fully rational investors and efficient markets cannot easily reconcile the observed short-horizon predictability and asymmetric return responses to optimistic versus pessimistic sentiment, reinforcing the limitations of traditional models already noted in earlier behavioral and sentiment-based work (Kamath et al., 2024; Beckmann et al., 2024).

In parallel, sentiment measurement up to 2024 has broadened from survey- and price-based indicators to more data-driven approaches, but still lacks a universal benchmark. Systematic review evidence documents substantial heterogeneity in how sentiment indices are constructed, including differences in data sources, weighting schemes and aggregation rules, which often produce divergent signals even for similar markets and horizons (Prasad et al., 2022). At the same time, new studies employing sentiment analysis and deep learning on news and social-media text report improvements in stock-return forecasting, while also revealing strong model- and context-dependence in the extracted sentiment measures (Akyüz et al., 2024; Hajek et al., 2025). Despite methodological advances, there is still no consensus on a single, universally accepted sentiment index, and disagreement over the dimensionality and structure of sentiment remains a central challenge for sentiment-based asset-pricing research (Prasad et al., 2022).

Research on the influence of google trends on stock performance in India has made significant strides, yet several gaps remain that could be addressed to enhance understanding of this relationship While existing studies have established a positive correlation between Google search volumes and stock indices, the underlying mechanisms causing this association are still not fully understood. Most research has focused primarily on descriptive statistics and correlation analyses without delving deeply into the specific contexts that might amplify these effects (Bijl et al., 2024). The current literature predominantly focuses on weekly data for long term trends due to ease in availability of the weekly data. By focusing on daily data, researchers can better assess the real-time impact of investor attention on stock prices, leading to more timely and informed trading decisions. Moreover, daily data allows for a more granular analysis of short-term market dynamics. By utilizing daily Google trends data alongside historical stock performance metrics, the present study can develop more robust models that account for immediate shifts in investor sentiment. And present study aims to contribute to the behavioral finance literature by validating the use of digital data sources specifically web search behavior as quantifiable metrics for understanding and forecasting investor sentiment in emerging markets.

RESEARCH METHODOLOGY

Purpose of the Study

By focusing on India's most widely tracked stock index NSE Nifty 50, this study provides insight into how retail and institutional investor behavior, reflected in search engine activity, may correspond with shifts in market performance. The primary objective of this study is to examine the relationship between web search query data measured by the Google Sentiment Index (GSI) and stock market returns of NSE Nifty.

Specifically, this study seeks to assess whether fluctuations in the frequency of Google search queries related to financial terms and market events can serve as a reliable and real-time proxy for investor sentiment, and whether such sentiment affects index fluctuations in a quantifiable way.

Research Design

This exploratory study investigates the correlation between web search-based query data as a direct proxy for investor sentiment and its impact on predicting returns in the Indian stock market. The study aims to determine whether web search-based query data, as measured by the Google Sentiment Index (GSI), can serve as a direct proxy for investor sentiment concerning Indian stock market returns.

The data is collected from secondary sources for financial time series and keywords identified as investor's sentiment proxy. The financial data for stock market returns and sectoral returns is collected from the NSE and BSE website. The data regarding the keywords identified for Google search is collected from the Google trends website and Trendecon R package.

Google Trends, launched in 2012 (evolving from Google Insights for Search introduced in 2008), is a data analytics service that provides normalized, relative search volume indices (0–100) for specific keywords across different regions, languages, categories, and search channels, allowing researchers to infer public attention and investor sentiment levels. The platform provides weekly data for up to five years, and monthly data for longer periods. Risteski and Davcev (2014) proposed a method to merge weekly and monthly series, but Volyublennaia (2014) noted that this approach did not yield reproducible results, recommending separate evaluation of five-year periods. Later, Eichenauer et al. (2020) developed the trendecon R package, which harmonizes multiple Google Trends queries (daily, weekly, and monthly) to generate stable, consistent, and long-term daily economic indices. The package ensures robustness by repeated querying and alignment of frequencies, preserving long-term trends and enabling the creation of real-time macroeconomic indicators such as confidence and activity indices. Thus, in this study, data are sourced using the trendecon R package to ensure stability and consistency across frequencies, addressing the normalization issues inherent in Google Trends data.

Financial keywords were selected using prior literature, Google Trends suggestions, and financial dictionaries such as Harvard IV-4 and Lasswell of the General Inquirer. Low-value terms were dropped. Following Preis et al. (2013) and Vosen & Schmidt (2011), correlation analysis was applied to retain terms strongly associated with market movements. Following the approaches of Brochado (2020) and Jung and Seo (2025), the final sentiment index in the present study is constructed by aggregating the shortlisted high-correlation keywords to capture investor attention.

$$GSI_t = \frac{1}{n}\sum_{i=1}^{n} SV_{i,t} \quad (1)$$

Where, GSIt represents the Google Sentiment Index at time t. SVi, t stands for the Search Volume for the ith keyword at time t. It indicates how frequently a specific term related to investor sentiment is searched on Google during time t, n is the total number of keywords used to construct the sentiment index.

The final GSI included keywords are, “Nifty 50”, “ Stocks”, “Sensex Today”, “Nifty 50 Today”, “Sensex Share Price”, “Bombay Stock Exchange”, “Nifty 50”, “Sensex”, “Sensex Share Price Today”, “Sensex Live Today”, “ Sensex Today India”.

The studied time span is of 14 years beginning from 1st January 2010 till 31st December 2023 with daily frequency. Initially for keyword collection R software is used and further for statistical analysis E- Views is used to analyze the impact of investor sentiment proxied by Google Sentiment Index on different quantiles of stock market returns by using Quantile Regression. While traditional linear regression models (like OLS) estimate the average effect of independent variables on the dependent variable, quantile regression enables the investigation of how the impact of investor sentiment varies across different points (quantiles) of the return distribution, such as during market booms (upper quantiles) or downturns (lower quantiles). This is particularly important in financial markets, where sentiment-driven behavior may have asymmetric effects—stronger during extreme market conditions. By applying quantile regression, this study aims to uncover whether Google search activity has a differential impact on stock returns in bullish, bearish, and neutral phases of the market. This approach provides a more comprehensive understanding of the sentiment-return relationship than mean-based models. To evaluate the lead lag relationship, Vector Autoregression (VAR), the causality method is applied individually between GSI and Indian stock market indices. The VAR analysis examine the impact of the previous lags of the GSI and stock indices market returns assumed as each of the series as endogenous variable in VAR system.

Data Analysis and Intrepretation

The relationship between Google Sentiment Index (GSI) indicating the web search query data in Google as a measure of investor’s sentiment and the stock index returns using NSE Nifty as index returns in India is determined with the help of descriptive analysis of the included time series variables (GSI, Nifty index, and Nifty returns). The unit root test is used to examine the nature of stationarity in each included time series. The correlation and regression analysis are applied for examining the linear relationship between the GSI and stock index returns. The quantile regression analysis is applied to find out the relationship between the quantile's movements within the series and finally the VAR methodology is used to examine the nature of causality between the GSI and stock index returns.

Table 1: Linear Regression - Dependent Variable: Nifty Return

	Daily data		
Independent Variable	Coefficient	SE	T Stats
GSI	-0.0003	0.0009	-4.120**
Intercept	0.002	0.0004	5.162**
F stats	16.975 (0.000)		
R Square	0.003		

*(Note: Table reports coefficients and t-values, where *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively) (Source: Self, Eviews generated)*

Table 2: Quantile Process Estimates Nifty Returns

Quantile Process Estimates Nifty Returns (Daily)					
	Quantile	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Google Sentiment Index	0.100	-0.00016	0.00002	-9.761	0.000
	0.200	-0.00009	0.00002	-5.358	0.000
	0.300	-0.00005	0.00001	-4.258	0.000
	0.400	-0.00004	0.00001	-3.812	0.000
	0.500	-0.00001	0.00001	-0.873	0.382
	0.600	0.00001	0.00001	1.181	0.237
	0.700	0.00003	0.00001	2.819	0.004
	0.800	0.00004	0.00001	3.044	0.002
	0.900	0.00007	0.00002	3.450	0.000
Constant	0.100	-0.0048	0.0006	-7.80	0.000
	0.200	-0.0028	0.0007	-4.020	0.000
	0.300	-0.0014	0.0004	-2.868	0.004
	0.400	0.0002	0.0004	0.698	0.484
	0.500	0.0010	0.0004	2.554	0.010
	0.600	0.0021	0.0004	4.479	0.000
	0.700	0.0037	0.0005	7.299	0.000
	0.800	0.0061	0.0005	11.076	0.000
	0.900	0.0088	0.0008	10.572	0.000

(Source: Self, Eviews generated)

The table presents the results of linear regression models to assess the relationship between GSI and Nifty return. The coefficient for GSI is statistically significant (p-value < 0.001), indicating a strong relationship between GSI and Nifty Return. The negative coefficient for GSI suggests an inverse relationship. This implies that as GSI increases, Nifty return tends to decrease, and vice versa.

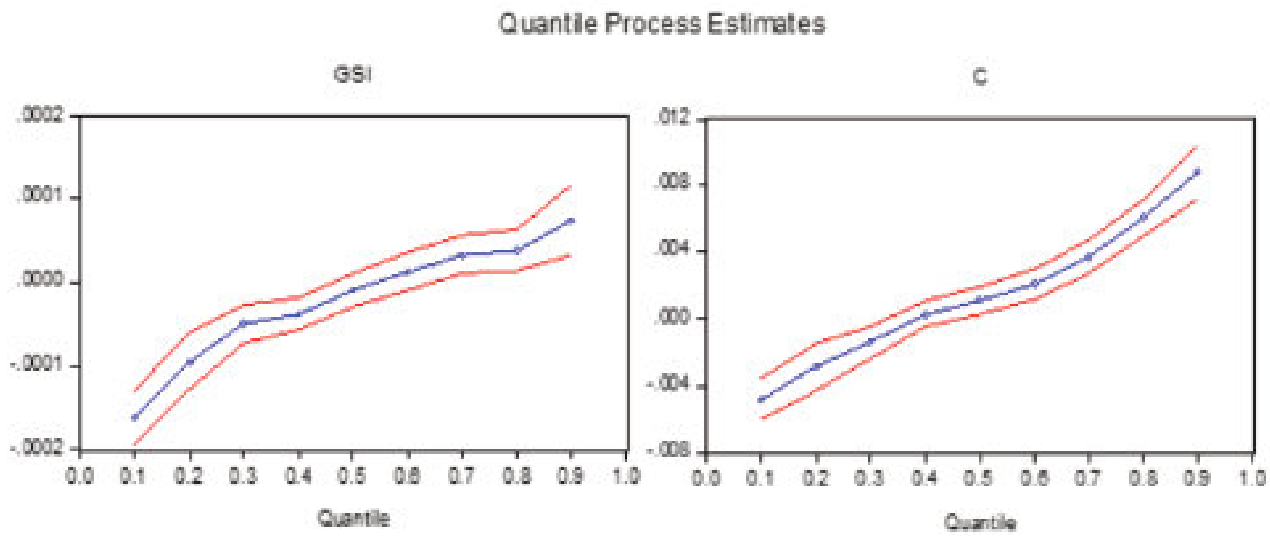
The linear regression provides the conditional mean of stock indices return using average values of GSI. However, the one of the major drawbacks of linear regression is the assumption of linear relationship and the possibility to ignore the multiple modes in stock indices returns. In such case the quantile regression is proved more effective as it can explain the stock indices behaviour at different percentiles due to the changes in different percentiles in GSI.

Quartile regression between Nifty and GSI

The estimated coefficients and quantile graph is reported in Table 2 and Figure 1.

The quantile regression results reveal that the impact of the Google Sentiment Index (GSI) on Nifty 50 returns varies across different points of the return distribution. At lower quantiles (0.10 to 0.50), the coefficients are negative and statistically significant, indicating that increased sentiment correlates with decreased returns during less favorable market conditions. This suggests that in bearish markets, heightened sentiment might coincide with lower returns indicating positive sentiment might lead to overvaluation and a subsequent correction. In the middle quantiles (0.50 to 0.60), the coefficients are not statistically significant, implying a weaker or negligible relationship between sentiment and returns. Conversely, at higher quantiles (0.60 to 0.90), the coefficients become positive and significant, showing that during bullish market conditions, higher sentiment corresponds to increased returns. Positive sentiment seems to coincide with higher Nifty returns during periods of strong performance (higher quantiles), indicating that positive sentiment may amplify gains in favorable market conditions. Overall, the analysis highlights that the influence of market sentiment on returns is not uniform but varies, becoming more positive as market performance improves.

Figure 1: Quantile Process Estimates Nifty Returns (Daily Data)



(Source: Self, Eviews generated)

The graph suggests that the effect of GSI on Nifty 50 returns varies across return levels, being more positive at higher quantiles, while the effect of constant is generally stable with slight increases at higher quantiles. This further supports the earlier finding that sentiment, as captured by GSI, may play a stronger role during periods of higher returns.

Quantile Slope Equality Test and Symmetric Quantiles Test

The results of Quantile Slope Equality Test and Symmetric Quantiles Test is reported in table no 3. The result reported that the slope of the quantile is not equal at the different quantiles, however maintains the symmetry at 25th and 75th quantiles. As a result, it can be said that the quantile regression approach is a more effective way to analyse the nonlinear relationship between the returns of the Nifty index and the GSI.

Table 3: Quantile Slope Equality Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test	39.84742	2	0.0000	
Restriction Detail: b(tau_h) - b(tau_k) = 0				
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**
0.25, 0.5	Google Trend	-0.00006	0.00001	0.0000
0.5, 0.75		-0.00004	0.00001	0.0000

(Source: Author's Own, Eviews generated)

Table 4: Symmetric Quantiles Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test	1.584488	2	0.4528	
Restriction Detail: b(tau_h) + b(1-tau) - 2*b(.5) = 0				
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**
0.25, 0.75	Google Trend	0.0000	0.0000	0.3820
0.5, 0.75	C	0.0008	0.0007	0.2631

(Source: Author's Own, Eviews generated)

Table 5: VAR Granger Causality/Block Exogeneity Wald Tests Nifty Return

Dependent variable: NIFTY Returns (Daily Data)			
Excluded	**Chi-square**	**Degree of freedom**	**Prob.**
GSI	14.302	7	0.0461
All	14.302	7	0.0461
Dependent variable: GSI			
Excluded	**Chi-square**	**Degree of freedom**	**Prob.**
NIFTY return	61.028	7	0.0000
All	61.028	7	0.0000

(Source: Author's Own, Eviews generated)

The Symmetric Quantiles Test indicates that there is no significant evidence to suggest that the distribution of the data is asymmetric around the median for the given time period (weekly). The test results support the hypothesis of symmetry, implying that the data is balanced on both sides of the central tendency.

Causality between Stock Indices (Nifty and GSI)

The VAR methodology begins with selection of the optimum lag length of the included GSI series and Nifty indices returns series. The lag length is selected using different lag length criteria (SC, AIC and HQ). The results of lag length selection criteria for incorporating the lags of the GSI series and Nifty indices returns series are contained in Table 5.

The results from the Granger causality tests reveal significant insights into the dynamic relationship between investor sentiment proxied by GSI and Nifty stock market returns. Where Nifty returns serve as the dependent variable shows a Chi-square value of 14.302 with 7 degrees of freedom and a corresponding p-value of 0.0461. Since this p-value is less than the 5% significance threshold, the null hypothesis that GSI does not Granger-cause NIFTY returns is rejected. This indicates that daily fluctuations in Google search interest significantly help predict Nifty market movements, suggesting that investor sentiment reflected in search behavior carries meaningful information for short-term return dynamics. Conversely, when GSI is taken as the dependent variable, the Chi-square statistic is 61.028 with a p-value of 0.0000, which is highly significant (Table 6). This result implies that daily market returns also Granger-cause changes in GSI, pointing to a bidirectional causal relationship. Thus, there exists a feedback loop on a daily basis where both investor sentiment and market returns influence each other.

Table 6: Variance Decomposition Function of Nifty Return & Google Trends

Variance Decomposition of Nifty returns Daily Data				Variance Decomposition of GSI Daily Data		
Period	**S.E.**	**Nifty return**	**GSI**	**S.E.**	**Nifty return**	**GSI**
1	0.0100	100.00	0.00	5.585	2.08	97.91
2	0.0104	99.91	0.08	6.037	2.62	97.37
3	0.0106	99.90	0.09	6.049	2.94	97.05
4	0.0106	99.88	0.11	6.073	3.23	96.76
5	0.0106	99.88	0.15	6.100	3.80	96.19
6	0.0106	99.87	0.12	6.127	4.27	95.72
7	0.0106	99.86	0.13	6.167	4.67	95.32
8	0.0106	99.86	0.13	7.141	4.19	95.80
9	0.0106	99.83	0.16	7.578	4.25	95.74
10	0.0106	99.83	0.164	7.624	4.45	95.54

(Source: Author's Own, Eviews generated)

The results depicts that the Nifty returns Indian stock market is explained by 99.835% with the help of its own lagged behaviour and only 0.164 % due to the GSI behaviour. However, in Table no. 6 the variance decomposition of GSI, the results reported the variance of GSI explained by 95.54% with the help of its own lagged behaviour and only 4.45 % due to the previous lags of Nifty returns. The strong self-explanatory nature of Nifty returns (99.8% at period 10) suggests that market movements are predominantly influenced by past market performance rather than sentiment. The increasing explanatory power of Nifty returns on GSI (from 2.08% in period 1 to 4.45% in period 10) highlights the significant role of past market performance in shaping sentiment over time.

DISCUSSION

The purpose of this research is to explore the intersection of digital behavior and financial market activity by utilizing Google trends data as a non-traditional, data-driven indicator of investor psychology in the Indian context. As investor sentiment plays a vital role in market dynamics often driving prices beyond what fundamentals would suggest capturing it through real-time online behavior offers a novel and practical approach to understanding market fluctuations.

Through the objective of examining the relationship of web search query data as a direct proxy or direct reflector for investor's sentiment with Nifty index returns in India, the study seeks to determine the extent to which web search trends reflect investor sentiment and influence the performance of Nifty returns in the Indian financial markets. This analysis highlights that the effect of sentiment on returns varies across the return distribution, with more pronounced effects in extreme market conditions. The results of a quantile regression analysis examining the relationship between Nifty 50 returns (dependent variable) and the Google Sentiment Index (independent variable) indicates that the relationship between index returns and the Google Sentiment Index (GSI) varies across different points in the return distribution. The effect of the GSI on index returns is not uniform. It has a significant negative impact during lower returns and a significant positive impact during higher returns, reflecting how market sentiment influences returns differently across various market conditions. The daily coefficients tend to be more sensitive, showing a stronger immediate relationship between sentiment and returns. Negative coefficients in the lower quantiles and positive in the higher quantiles indicate significant short-term impacts of sentiment.

The results of the Vector Autoregression (VAR) model for daily data suggest a bidirectional relationship between the GSI and index returns, but with differing levels of statistical significance. The findings indicate a feedback relationship between GSI and index returns. However, the stronger significance of index returns in predicting GSI suggests that market movements may have a greater impact on sentiment than sentiment has on market movements. This aligns with the idea that investors react strongly to past market performance when forming sentiment, while sentiment itself, though influential, has a comparatively weaker effect on future returns. This suggests that sentiment is largely influenced by stock returns rather than the other way around, reinforcing the idea that investors' mood depends on how the market has performed recently.

The variance decomposition results highlight the differing roles of investor sentiment (GSI) in explaining index returns across daily timeframe. In the daily data, index returns are almost entirely self-driven, with GSI contributing very minute to the variance by the tenth period. This suggests that short-term market fluctuations are largely independent of sentiment, and other market factors such as macroeconomic news, institutional flows, and technical indicators drive daily returns. Similarly, GSI itself is predominantly influenced by its past values, with index returns explaining only few percentage points of its variance over time. This indicates that while market performance does have some influence on daily sentiment, the effect is relatively weak.

The key takeaway is that daily market movements are primarily driven by internal price dynamics, and sentiment indicators alone are not strong predictors of short-term returns. This suggests that traders and investors considering sentiment-based strategies should focus on longer holding periods rather than intraday movements.

CONCLUDING OBSERVATIONS

The rising prominence of behavioral finance has brought investor sentiment to the forefront as a critical factor influencing stock market dynamics, particularly those anomalies and fluctuations not adequately explained by traditional financial theories. In this evolving landscape, the use of alternative data sources has opened new avenues for understanding market behavior. Among these, Google trends offers a novel, real-time, and publicly accessible proxy for gauging investor attention and sentiment. Google search trends can act as early warning signals for financial instability or systemic risk. This study demonstrates that Google trends derived GSI serves as a viable proxy for investor sentiment in Indian markets, with effects on Nifty 50 returns varying by market regime—stronger in extremes via quantile regression. However, daily dynamics reveal returns primarily drive sentiment (per VAR), not the reverse, and sentiment explains negligible short-term variance. Traders should prioritize longer horizons for sentiment strategies, as daily fluctuations rely more on internal price momentum, macro news, and institutional flows than online search behavior. A sudden surge in queries for terms like "default," "bankruptcy," "stock market crash," or "financial crisis" may indicate rising anxiety among market participants or the public. Risk managers can use such sentiment data to proactively assess vulnerabilities in their portfolios. By recognizing sentiment-driven warning signs early, they can implement defensive strategies such as rebalancing portfolios, increasing hedging positions, or reducing exposure to high-volatility assets. This approach adds a behavioral layer to traditional risk management, allowing for a more dynamic and psychologically informed understanding of market threats. GSI provides actionable insights for both investors and policymakers in navigating Nifty 50 dynamics. Investors benefit from real-time sentiment proxies to time trades in extreme market regimes, integrate into risk models for volatility forecasting, and adopt longer-term strategies given weak daily predictive power. Policymakers like RBI/SEBI can monitor for bubbles/panics, calibrate interventions during downturns, and use it alongside traditional indicators to enhance market stability and promote fundamentals-driven reforms. Overall, it bridges behavioral data with policy, fostering resilient Indian markets amid sentiment fluctuations. This research will help bridge the gap between traditional financial models and modern behavior-based approaches, demonstrating how publicly available search data can enrich investment analysis, portfolio strategy, and market forecasting in the Indian financial ecosystem.

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