Investigating the Impact of Social Media-Driven Sentiment on the Electric Vehicle Stock Market Using Quantile Regression

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ABSTRACT

The electric vehicle (EV) sector has experienced remarkable growth, fueled by technological advancements, government incentives, and increasing environmental awareness. As the world shifts towards a low-carbon economy, EVs play a crucial role in reducing carbon emissions and shaping sustainable investment portfolios. This study investigates the impact of consumer sentiment on EV market performance, with a particular focus on social media platforms like Reddit. By constructing sentiment indices from user-generated content, the research applies quantile regression analysis to explore the relationship between social media-driven sentiment and sectoral stock returns. Unlike traditional models that focus on average market behavior, quantile regression captures the distributional effects of sentiment, particularly at the extremes, offering deeper insights into market volatility. The findings reveal how shifts in consumer sentiment, driven by emotional and behavioral factors, can significantly influence EV stock prices, providing valuable insights for investors and policymakers. This study contributes to the growing field of sustainable finance by introducing a novel approach to understanding how social media sentiment can guide investment decisions in the rapidly evolving EV sector, thereby supporting the transition to a more sustainable economy.

Keywords: Sentiment Analysis, Electric Vehicle, Quantile Regression
JEL Classifications: C45, Q42, C31

1. INTRODUCTION

Electric vehicles (EVs) play a crucial role in the clean energy transition by aligning with sustainability goals like reducing carbon footprints and lowering greenhouse gas emissions (Chen and Ma, 2024). This makes EV stocks essential in sustainable investment portfolios. The EV sector is closely linked to green finance through mechanisms such as green bonds, ESG criteria, and sustainability-linked loans (Zairis et al., 2024). These tools support EV manufacturers and attract sustainable investors. Government incentives further enhance this environment by reducing consumer costs and encouraging investments in cleaner energy (Qadir et al., 2024). As institutional investors increasingly prioritize

ESG standards, EV companies that demonstrate commitment to environmental and social responsibility become more attractive, fostering the sector's integration into the broader sustainable finance ecosystem (Kim and Li, 2021). Promoting EV adoption, governments and investors contribute to reducing carbon emissions and advancing a low-carbon economy, making EV stocks integral to both environmental and financial sustainability (Tilly et al., 2024). The EV industry has experienced unprecedented growth over the past decade, driven by technological advancements, government policies, and rising consumer awareness about environmental sustainability. As the demand for EVs continues to surge globally, understanding the factors that influence this demand and its impact on market performance has become increasingly vital (Cao et al.,

2021). Thus, analyzing EV sector performance offers valuable insights into future market trends, investment opportunities, and the impact of macroeconomic factors, making it a critical area of study in the context of global economic and environmental challenges.

Moreover, the connection between EV demand and sectoral stock returns is shaped by various factors, including financial market reactions, consumer behavior, and broader macroeconomic trends. Understanding this relationship is essential for investors, businesses, and policymakers, as shifts in demand can influence market confidence, corporate profitability, and stock performance. This relationship can be examined through direct impacts where rising demand boosts revenues and stock prices and indirect influences, such as economic policies, interest rates, and oil prices, which shape market expectations. As seen in Table 1, the direct link between EV demand and stock market performance is shaped by actual sales figures, market expectations, and production efficiency. While strong demand generally supports higher stock prices, speculative investments and supply chain dynamics can create volatility and short-term market fluctuations. Understanding this relationship is appealing for investors, as tracking EV demand trends provides key insights into stock price movements, enabling better-informed financial decisions. The macroeconomic factors and government regulations significantly influence the performance of the EV sector. While policy incentives and increased oil prices typically stimulate demand and drive stock values higher, rising interest rates and cuts in subsidies may hinder growth and contribute to market volatility. To stay ahead of these fluctuations, investors, automakers, and policymakers need to closely track economic trends and legislative changes, allowing them to adjust their strategies accordingly. As the EV market expands, having a comprehensive understanding of how financial conditions, energy prices, and regulatory frameworks interact will be essential for mitigating risks and identifying profitable opportunities in an ever-changing investment environment.

This study aims mainly to analyze the impact of sentiment indexes, created based on user comments from the Reddit social media platform, on the performance of the EV sector only within the framework of the direct impact channel. Social media provides a significant alternative indicator for measuring market sentiment, complementing traditional financial indicators. The real-time flow of information, sentiment analysis, and psychological effects allow social media to become a powerful tool in shaping market dynamics. While positive and negative tones on social media can rapidly influence market movements, investors can analyze this data to develop portfolio strategies and manage their risks.

The study investigates how consumer demand shapes the EV sector and the effects of these demand dynamics on stock market performance. Despite growing interest in the influence of social media on financial markets, there is a significant gap in understanding how sentiment from platforms like Reddit directly influences EV market performance, especially when analyzed through advanced econometric models such as quantile regression. The contributions of this study can be summarized as follows. Firstly, this study examines perceptions of EV by analyzing user discussions on Reddit, a dynamic and interactive platform. Unlike traditional analyses that rely on conventional data sources, this approach highlights the value of social media insights in understanding consumer behavior and EV demand. Secondly, Reddit offers real-time, in-depth user interactions and sentiment insights, making it a valuable source for tracking consumer opinions, emotions, and demand-related preferences. The data obtained from this platform enables the development of sentiment-based indexes, distinguishing between positive and negative sentiments, as indicators of EV demand. Finally, using social media data for emotional and behavioral analysis, this study investigates the relationship between EV demand and sectoral returns in a quantile regression model that enables a more precise

Table 1: Interaction channels of EV Demand and stock market returns

Effects	Channels	Interaction mechanism	Example
Direct effects	Sales volume	As EV demand grows, automakers see higher profits, boost investor confidence and stock valuations.	In 2020, Tesla's sales surged, driving up its stock price and strengthening investor confidence.
	Consumer expectations	The EV sector is seen as high-growth, leading investors to value stocks based on future sales rather than current earnings.	In 2021, investors flocked to EV startups like Rivian and Lucid, betting on long-term growth despite limited production.
	Production capacity	Rising EV demand pushes automakers to expand production and boost long-term profitability.	In 2022, Tesla expanded production in China, boosting revenue and stock performance as investors saw it as a sign of continued growth.
Indirect effects	Government incentives and tax benefits	Governments worldwide offer tax breaks, subsidies, and infrastructure investments to improve EV adoption, reducing upfront costs and increasing consumer appeal.	The Inflation Reduction Act (IRA) in the U.S. (2022) extended EV tax credits, leading to a surge in market confidence for automakers like Tesla and General Motors.
	Oil prices	Rising fuel prices reduce the appeal of gasoline vehicles and drive consumers toward EVs as a cost-effective alternative.	In 2022, rising oil prices from geopolitical conflicts boosted EV sales, driving positive stock momentum for Tesla and BYD.
	Interest rates and financial conditions	High interest rates raise borrowing costs, making auto loans expensive and discouraging EV purchases or vice-versa.	In 2023, the U.S. Fed hiked interest rates, lowering EV stock valuations as investors shifted to safer asset.

prediction of financial asset price movements, especially when high-frequency market data is available. This ability to analyze the tail behavior of the distribution makes quantile regression an essential tool for forecasting market trends and understanding the risk and volatility of financial assets in a more comprehensive manner than the others. Unlike previous studies, and to the best of our knowledge for the first time, this research offers a novel perspective on predicting sector performance fluctuations by utilizing emotional and behavioral analysis of user-generated content as an input for econometric analysis. In doing so, it generates a unique, previously unexplored dataset and integrates it into an econometric framework, making a significant contribution to the literature.

Following the introduction, the study will be organized into several key sections. The literature review will explore existing research on EV demand, consumer sentiment analysis, and sector performance, highlighting the gaps in current literature and the unique contribution of this study. The next section, data and methodology, will detail the sources of Reddit user comments and the sentiment analysis techniques used to construct sentiment indexes. This section will also describe the econometric models and methods for analyzing the impact of consumer sentiment on EV sector performance. In the results and discussion section, the relationship between social media sentiment and sectoral returns will be examined, with particular emphasis on the findings from the quantile regression analysis. This section will interpret the positive and negative sentiment effects on the EV market and provide a detailed discussion of the results. Finally, the conclusion will summarize the study's main findings, discuss the implications for investors and policymakers, and suggest future research directions in the field.

## 2. THE DYNAMICS OF ELECTRIC VEHICLE MARKET

Electric vehicles are increasingly considered a promising sustainable alternative to internal combustion engine vehicles. As environmental awareness rises globally, the market demand

for EVs has been steadily growing, leading to rapid growth in the electric vehicle market. With the expected increase in EV adoption, the market size for electric vehicle components and materials is anticipated to expand as well. As of 2023, global EV sales have reached 14 million, with the total number of electric vehicles on the road surpassing 40 million worldwide. Of these sales, 95% occurred in China, Europe, and the United States, reflecting a 35% increase compared to 2022. Electric vehicles now represent 18% of total car sales, with battery electric vehicles (BEVs) accounting for 70% of the total electric vehicle stock. These figures clearly indicate the rapid growth of the electric vehicle market and significant progress in the industry (IEA, 2024). According to the International Energy Agency's (IEA, 2024) report, a visual representation of annual vehicle sales is shown in Figure 1.

Figure 2 highlights that in the first half of 2022, the low category was dominant, while significant increases in the medium and high categories were observed, especially from the second half of 2022. These increases may reflect a period of rapid growth in the electric vehicle market, possibly driven by government incentives and technological advancements. In the first quarter of 2023, a decline in EV sales values occurred, which may be attributed to global economic uncertainties and supply chain issues. However, by the middle of 2023, an increase in the high category was observed again, suggesting a market recovery and the overcoming of challenges. From the beginning of 2024, a more stable trend in the medium and high categories has been observed. This can be explained by the maturing of the electric vehicle sector, increased consumer adoption, and improvements in charging infrastructure. This process indicates that the electric vehicle market has begun to reach a broader audience, ensuring stable growth.

The increase in EV sales is associated with various factors such as technological advancements, rising environmental awareness, and supportive government policies (Yan, 2023; Wu et al., 2022). Primarily, consumer awareness and interest play a critical role in the adoption of electric vehicles. Cahyati and Munandar (2023) shows that consumers' willingness to purchase EVs significantly increases as they become more aware of the environmental

Figure 1: Electric vehicle sales
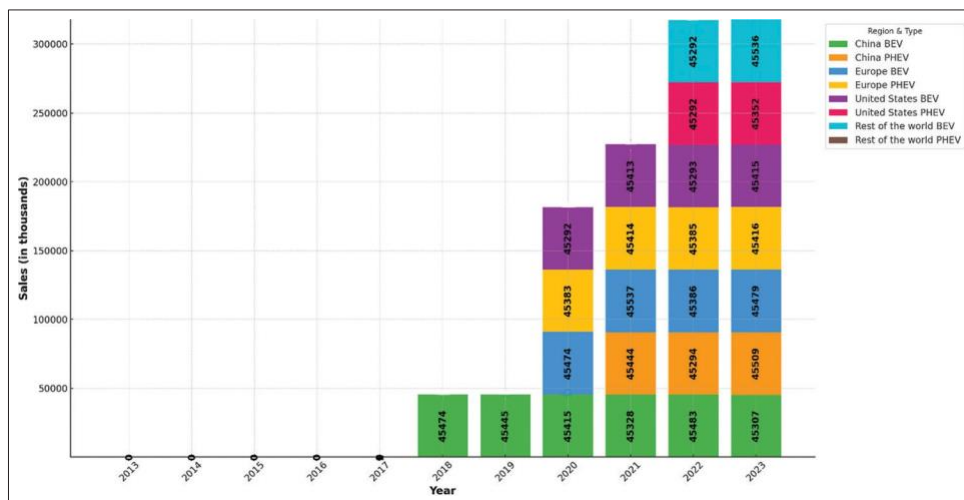
Source: IEA , 2024

Figure 2: The changes over time of EV sales
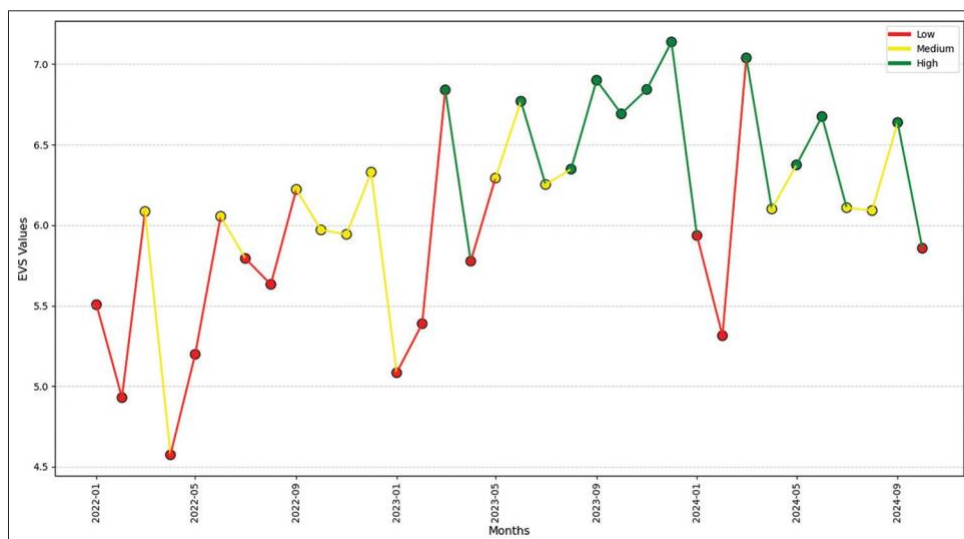
Source: MarkLines, 2024

benefits associated with these vehicles. Additionally, perceived environmental benefits and financial incentives have been shown to be important motivating factors for potential buyers (Dixit and Singh, 2022; Desai et al., 2019). In this vein, environmental concerns have been identified as one of the key factors influencing EV purchase intentions (Lai et al., 2015; Khurana et al., 2020) and the growing recognition of the need to reduce carbon footprints and combat climate change has made EVs a more attractive and cleaner alternative compared to traditional internal combustion engine vehicles (Wu et al., 2022). These findings align with studies reporting that global EV sales have doubled due to the increase in consumer awareness and the rapid development of EV technology and infrastructure (Razmjoo et al., 2022).

Government policies and incentives also play a crucial role in increasing EV sales. Many governments around the world have implemented subsidies and incentives to promote the adoption of electric vehicles (Wu et al., 2022). These policies not only reduce the initial costs for consumers but also support the development of necessary charging infrastructure to address range anxiety for potential buyers. Additionally, significant government support facilitating global EV adoption emphasizes the importance of policy frameworks in this transition (Razmjoo et al., 2022). On the other hand, technological advancements, particularly in battery technology and charging infrastructure, have significantly contributed to the growth of EV sales (Razmjoo et al., 2022; Muratori et al., 2021). The development of fast-charging stations and improvements in battery efficiency have made EVs more practical for daily use by addressing previous concerns regarding charging times and vehicle range (Razmjoo et al., 2022; Muratori et al., 2021).

Moreover, societal attitudes towards sustainability and climate change have shifted, with many consumers increasingly opting for environmentally friendly options in their purchasing decisions (Lai et al., 2015; Khurana et al., 2020). In addition, social media platforms play a role as a medium for emotional interactions, directly influencing consumers' purchasing decisions.

Emotional content shared on social media not only strengthens brand perception but also enhances consumer trust, playing a critical role in shaping purchasing behavior. Pai and Liu (2018) indicate that social media marketing can significantly increase purchase intentions by generating positive emotional responses in consumers. This research utilizes sentiment scores from tweets and stock market data to forecast monthly vehicle sales in the USA. The findings indicate that incorporating both social media sentiment and stock market values enhance the accuracy of vehicle sales predictions and suggest that public sentiment could be a valuable indicator in predicting sales trends in the industry.

In the automotive industry, the dynamics of "brand love" are increasingly shaped by digital media interactions, with consumer perceptions having a significant impact on purchasing intentions (Hashem et al., 2024). Social media, by fostering emotional connections with consumers, can support purchase intentions, while brands that strategically balance emotional and informational content can more effectively engage consumers and stimulate sales (Liadeli et al., 2022; Bulkis and Puspaningrum, 2021). The emotional impact of content shared on social media plays an important role in shaping consumer perceptions and decision-making processes, with consumer trust emerging as a critical mediating factor in the relationship between emotional interaction and purchase decisions (Zanjabila et al., 2023). Additionally, participation in social media brand communities has been shown to increase consumer spending and emotional-informational content shared within these communities strongly influences consumer demand (Goh et al., 2013).

In conclusion, the rapid growth of the electric vehicle (EV) market, fueled by technological innovations, government incentives, and rising environmental awareness, underscores the pivotal role of EVs in the global shift towards sustainable transportation. This study highlights the critical factors driving EV adoption, such as consumer awareness, government policies, and technological advancements, which together create a conducive environment for growth. Additionally, the role of social media as a powerful

tool for gauging consumer sentiment is becoming increasingly evident, with emotional content shared online influencing purchasing decisions and market trends. The integration of social media sentiment analysis, alongside traditional market indicators, offers a more dynamic approach to forecasting EV sales and market performance. As consumer confidence in EVs grows and technological challenges continue to be addressed, the market is expected to mature and reach a broader audience. Policymakers and businesses can leverage insights from both sentiment analysis and market trends to design strategies that further support the adoption of EVs and drive the industry towards a more sustainable future. Ultimately, this study provides a comprehensive framework for understanding the intricate relationship between consumer sentiment, market trends, and the future of the electric vehicle sector.

3. LITERATURE REVIEW

EVs and social media sentiment hold a significant place in contemporary research. In addition to the environmental impacts of electric vehicles, consumer perceptions, purchase decisions and market trends are fundamental factors shaping the future of the sector. In this context, recent studies have provided insights into better understanding consumer emotions, user experiences, and market dynamics related to EVs. On the other hand, the influence of social media platforms on investor behavior has also garnered increasing attention. Social media sentiment, in particular, has a substantial effect on stock markets, influencing investor decisions and market volatility. This section examines the existing literature on text mining for EV-related sentiment and the impact of social media sentiment on financial markets, analyzing how the intersection of these two dynamics influences the sector.

3.1. Sentiments on Electric Vehicles

In recent years, text mining has emerged as a powerful tool in EV research, enabling the extraction of valuable insights from unstructured data research on consumer sentiments and perceptions regarding EVs has been steadily increasing. Puspita et al. (2024) systematically reviewed text mining studies on EVs conducted between 2011 and 2023, focusing on trends related to customer awareness, satisfaction, and policy impacts. In their study, sentiment analysis, Latent Dirichlet Allocation (LDA) and social network analysis were identified as the most commonly used text mining techniques in EV research. Most studies have focused on analyzing social media, user experiences, and EV-related reports (Puspita et al., 2024). They have explored various aspects of consumer sentiments and experiences with EVs, often using advanced text mining techniques to analyze online data. Zou et al. (2024) analyzed online comments to gain insights into user experiences with EVs.

Similarly, Liu and Xie (2024) examined the evolution of policies related to China's EV industry by reviewing national and local government policy documents between 2009 and 2023. Trinko et al. (2021) investigated EV charging prices in the United States using data from the PlugShare platform, revealing how prices vary based on charging levels, geographic locations, network providers, and types of locations. Liang et al. (2024) proposed a novel Failure Modes and Effects Analysis (FMEA) method that integrates text mining and multi-perspective group consensus to identify product defects and assess safety performance in EV-related social media data. Mukundan et al. (2019) applied text mining to analyze stakeholders' responses to the Indian government's EV policy, categorizing reactions into shaping, supporting, opposing, and delaying the policy. Gu et al. (2022) conducted a similar text mining analysis on two popular battery electric vehicle (BEV) models in China—Tesla Model 3 and BYD Han EV—evaluating user experiences in terms of vehicle hardware, software, and subjective feelings, and offering AI-assisted suggestions to enhance user experience. Carpenter et al. (2014) developed a system to extract and analyze opinions from online forums, focusing on both positive and negative comments about EV features and long-term user perceptions. Wang et al. (2022) analyzed qualitative data on user experiences with EV sounds, identifying five key user experience dimensions (speed, mode, vehicle component, environment, and sound type) and offering suggestions for EV sound design improvements. In a similar vein, Demirer and Büyükeke (2022) utilized text mining, sentiment analysis and topic modeling to analyze Twitter comments on Turkey's TOGG-branded electric vehicle, shedding light on consumer perceptions.

Some other studies have explored various technical and operational aspects of EVs. Das et al. (2023) examined complaints from the U.S. National Highway Traffic Safety Administration's database to understand technical and body-related issues with hybrid electric vehicles (HEVs). Eldeeb and Mohamed (2022) performed Latent Dirichlet Allocation (LDA) analysis on 340 abstracts published between 2000 and 2021 to identify emerging research topics and gaps in electric bus (e-bus) development, adoption, and operation. Ma et al. (2019) used big data and text mining to analyze Chinese consumers' online behaviors regarding EV preferences. Lastly, Ding et al. (2023) developed a combined forecasting model using online reviews to improve predictions of EV product sales.

Among the common concerns are vehicle failures, poor service quality, weak battery performance in cold weather (Zou et al., 2024), and long waiting times at charging stations (Krishna, 2021), all contributing to psychological range anxiety (Franke et al., 2012). Enhancing charging infrastructure is essential to alleviating range anxiety (Ivanova and Moreira, 2023; Murugan and Marisamynathan, 2022; Neubauer and Wood, 2014). Consumers place greater importance on charging time than on range or battery capacity, with long charging durations being a primary cause of range anxiety (Ma et al., 2019). Therefore, manufacturers should prioritize faster charging technologies over larger battery capacities. Despite rapid advancements in EV development, driven by improvements in battery and charging technologies and government subsidies (Zhou et al., 2020), incentives have not yet sufficiently attracted a large number of consumers (Jena, 2020). Many users still prefer traditional vehicles over EVs due to the time-consuming nature of charging and the limited availability of charging stations (Glerum et al., 2014; Jena, 2020). Furthermore, battery replacement remains a significant issue, contributing to higher overall ownership costs (Krishna, 2021), while battery health is heavily dependent on storage and usage conditions

(Pelletier et al., 2017). There is also a debate about noise, with some arguing that EVs need noise for safety purposes (Bräunl, 2012), while others see the lack of noise as a potential safety concern (Krishna, 2021). Trust in EVs is increasing, but overall trust in EV technology remains lower compared to general technological trust (Bhalla et al., 2018). Despite the growing trust, negative emotions about EVs persist. In classification analysis, *anticipation* and *anger* were identified as the most influential factors in model prediction performance, suggesting that EVs are failing to meet consumer expectations when compared to traditional vehicles (Murugan and Marisamynathan, 2022). In spite of advancements in battery and charging technologies, consumers still prefer traditional vehicles over EVs, primarily due to long charging times and the limited availability of charging stations (Glerum et al., 2014; Jena, 2020). In conclusion, it is emphasized that EV manufacturers should prioritize investments in charging infrastructure and reducing charging times over increasing battery capacity. Although there are varying views on EV safety, improving safety and ensuring consumer trust remain crucial (Bräunl, 2012; Krishna, 2021).

In recent years text mining has become a pivotal tool in driving advancements in EVs with applications ranging from battery safety and performance improvements to analyzing consumer perceptions and environmental impacts. Nan et al. (2022) proposed a novel approach that combines short text mining with grey correlation analysis to identify error information in maintenance documents. In a similar context, Zhao and Sun (2022) employed big data analysis to study battery failures in real-world EV applications, highlighting the importance of understanding the relationship between battery performance and external parameters. Ju et al. (2021) investigated the factors influencing the adoption of environmentally friendly vehicles in Korea by analyzing news articles and online posts. He and Zhang (2021) used text mining techniques to extract valuable insights from existing literature, identifying new materials that could enhance energy storage solutions for EVs. Das et al. (2018) conducted exploratory text mining on user complaint reports to uncover significant vehicle defects, demonstrating how such insights can guide manufacturers toward targeted improvements.

Consumer sentiment plays a pivotal role in shaping the adoption and market dynamics of EVs (Schuitema et al., 2013; Moons and De Pelsmacker, 2012). Understanding how consumers perceive EVs including their concerns and expectations is essential for both manufacturers and policymakers. Social media platforms provide a rich source of real-time consumer feedback (Zou et al., 2024), offering insights into attitudes and preferences (Lin and Wu, 2018; Zhang et al., 2018; Krishnan and Koshy, 2021; Lee et al., 2021; Thananusak et al., 2017; Montian and Suthikarnnarunai, 2018) and potential barriers to adoption (Junquera et al., 2016; Jenn et al., 2020; Junquera et al., 2016; Yang and Tan, 2019; Miwa et al., 2017; Cecere et al., 2018; Jenn et al., 2020). Analyzing these sentiments, researchers have identified key factors that influence EV purchase decisions and the prevailing challenges that shape public perception. For example, negative sentiments towards EVs are more common than positive ones as in India where most EV-related social media comments were negative (Jena, 2020; Zou et al., 2024).

3.2. The Role of Social Media Sentiment in Stock Market Dynamics

Social media platforms have become key sources of information, shaping investor sentiment and stock market performance. Numerous studies have examined the relationship between social media sentiment and stock returns, emphasizing the role of investor emotions in shaping market dynamics. Recent studies have extensively examined the influence of social media and financial news on stock market performance, highlighting their impact on investor sentiment, market volatility, and trading volume. Verma and Verma (2025) analyzed the effects of economic news and social media sentiment on the DJIA, S&P 500, NASDAQ and Russell 2000 index returns. Their findings revealed that economic news sentiment had a stronger, positive impact, while social media sentiment created negative effects due to increased noise. Agarwal et al. (2021) studied the relationship between Twitter sentiment and stock indexs in India, finding small but significant impacts on the banking and finance sectors, with negative content leaving long-lasting effects on stock returns. Fan et al. (2020) explored the impact of social media bots on stock performance and found that while bot activity influenced volatility and trading volume, its effect on stock returns was limited. In a different study, Fan et al. (2020) investigated political uncertainty during the 2016 U.S. Presidential Election and Trump's inauguration, showing that the levels of disagreement among social media users were linked to stock volatility and trading volume. Li et al. (2014) developed a framework to analyze the impact of financial news on stock prices, showing that sentiment analysis models outperformed bag-of-words models. However, they found that relying solely on positive and negative sentiment was ineffective. Siganos et al. (2014) used Facebook's Daily National Happiness Index to analyze the relationship between sentiment and stock returns, finding that negative sentiment increased trading volume and volatility. Liu et al. (2015) analyzed the comovement of stock returns using firm-specific social media metrics, showing that firms with official Twitter accounts had higher comovement and social media metrics provided more accurate predictions than traditional industry classifications.

Like the studies mentioned above, another stream of research has explored the direct impact of investor sentiment, particularly happiness levels and social media sentiment, on stock returns, revealing unique effects across various markets and trading conditions. You et al. (2017) investigated the predictive power of investor sentiment, based on daily happiness data from Twitter, on stock returns across 10 international markets, finding that investor sentiment only affected stock returns in high quantile ranges. Zhang et al. (2016) found a stronger correlation between stock returns and happiness data on days of higher happiness, with happiness levels influencing stock performance across seven stock markets. Zheludev et al. (2014) showed that sentiment data from Twitter could significantly predict future prices, particularly for the S&P 500 index, providing more information than volume-based analyses. Nyakurukwa and Seetharam (2024) analyzed sentiment data from news and social media and found that social media sentiment had a significant effect on stock returns in the U.S. market, whereas news media had a more significant impact in other markets. Agarwal and Goel (2020) studied the impact

of news media information on stock markets in India and found that sentiment from specialized media sources showed significant correlations with specific indexes. Agarwal et al. (2019) reviewed the effects of information spread through internet news and social media on retail investors' trading patterns and stock market performance, emphasizing the need for further research, especially in emerging markets.

Similar to previous studies examining the influence of social media and investor sentiment on stock market dynamics, emerging research has begun to explore the role of user-generated content (UGC) and network effects in shaping financial trends, particularly in the EV sector. Van Dieijen et al. (2020) examined the relationship between UGC and stock market volatility, demonstrating that UGC volatility influenced market volatility, particularly during new product launches. In contrast to traditional studies focusing on economic indicators and sales data, research on the financial performance of the EV sector has been limited in considering social media sentiment. For instance, Li et al. (2017) examined the distribution of EV sales and charging stations across 353 metropolitan areas between 2011 and 2013, revealing how charging stations positively impacted EV sales and market spread through indirect network effects. Their findings highlighted that investments in charging station infrastructure were crucial in increasing EV demand, especially in the early stages. However, the impact of social media data on the EV sector remains relatively underexplored, despite its potential to influence investor sentiment and market behavior.

3.3. Literature Gap

The existing literature highlights the crucial role of consumer sentiment in the adoption and market performance of EVs, with social media emerging as a key source of real-time insights. While traditional studies have primarily focused on economic indicators and technical factors such as performance, charging time, and driving range, recent research underscores the growing influence of public sentiment, particularly as expressed on platforms like Twitter. Negative perceptions often dominate social media discussions, shaping consumer attitudes and influencing sectoral performance. Furthermore, studies suggest that user-generated content can significantly impact stock market volatility and

sales predictions, reinforcing the need for manufacturers and investors to integrate sentiment analysis into their decision-making processes. However, despite these advancements, gaps remain in the literature, particularly regarding the integration of social media sentiment into econometric modeling for predicting EV demand and market trends. Addressing these gaps through innovative methodologies, such as text mining and econometric analysis, can offer valuable insights for both industry stakeholders and policymakers.

Building upon the insights from previous research, our study takes a different approach by incorporating sentiment analysis to examine the relationship between sentiment indexes and EV-related market indexes. We employ a time series quantile regression analysis to assess the effects of social media sentiment on market behavior. By combining text mining techniques for feature extraction with quantitative analysis, our study differentiates itself from prior studies in the field. This integrated approach allows for a more comprehensive understanding of sentiment in dynamic sectors like electric vehicles, enabling more accurate predictions of market trends and financial performance. Furthermore, by leveraging econometric inference, we ensure that our analysis captures not only correlations but also the broader relationships, strengthening the reliability and policy relevance of our findings.

4. RESEARH PROCESS AND DATA

The research process mainly consists of text mining, data compiling and economic modeling stages. An overview of the research process is presented in Figure 3.

Figure 3 illustrates the transition process from sentiment scores obtained through text mining to economic modeling. First, in the text mining stage, sentiment analysis is performed on data derived from Reddit comments after undergoing various preprocessing steps. Second, sentiment analysis results in the creation of a Positive Sentiment Score Index (PSS) representing positive emotions and a Negative Sentiment Score Index (NSS) representing negative emotions. Additionally, sectoral indexes with strong representation of the electric vehicle (EV) sector are

Figure 3: From text mining to economic modeling
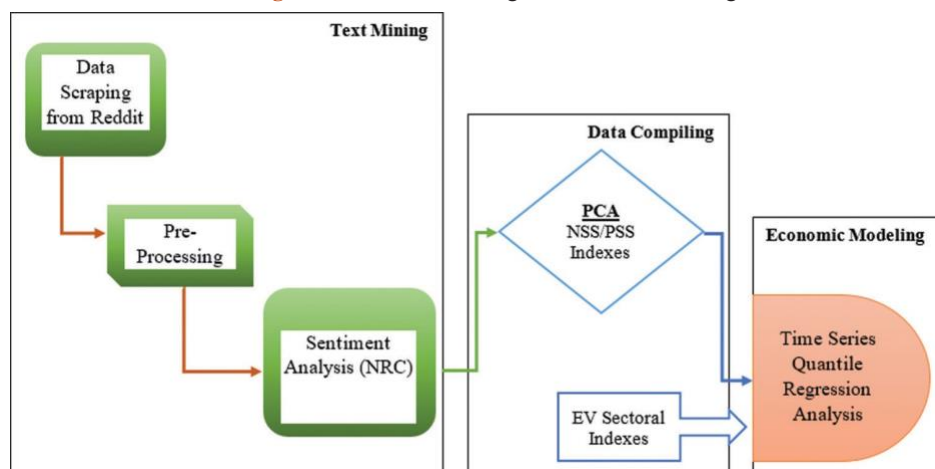
selected, and relevant data are compiled. The final stage involves constructing a model and conducting regression analysis to examine the impact of the developed sentiment indexes on the sectoral indexes.

4.1. Reddit as a Data Source

The influence of social media on market dynamics is shaped by a variety of factors, with the reactions of investors, analysts, and other market participants being significantly affected by the content shared on these platforms. Social media enables real-time information flow, providing much faster response times than traditional financial data. News that spreads through social media, such as positive developments related to a company (like new deals or product launches), can trigger immediate market reactions. Investors quickly notice such information, leading them to buy stocks and drive price movements in real time. Social media can also have a major impact on investor decision-making. By monitoring comments, news, and discussions on these platforms, investors can make swift buy or sell decisions. This rapid response is particularly important for traders using digital platforms. Consequently, the sentiment expressed on social media can reflect and amplify market speculation and uncertainties, influencing trends and behaviors at a faster pace. During times of crisis, social media has the potential to spread panic-driven news, creating a "fear, uncertainty, and doubt" (FUD) effect that can lead to significant market fluctuations. In these periods, markets become more sensitive to psychological pressures, and negative content circulating on social media can quickly lead to sell-offs. The increased sensitivity of the market to social media during crises highlights the power these platforms hold in shaping financial outcomes in volatile conditions.

This study analyzes user comments on the Reddit platform regarding EV to examine the relationship between consumer perceptions, emotional tendencies, and EV sales. The research uses Reddit comments from 2016 to 2024. User comments on Reddit were chosen as a natural data source that reflects emotions and thoughts about various aspects of electric vehicles. The emotional data extracted from the comments are categorized primarily into positive and negative sentiment. Additionally, the changes over time in eight different types of emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust) and how these emotions affect fluctuations in the electric vehicle sector indexes have been analyzed.

The data was collected using the Python Reddit API Wrapper, which enables the rapid and systematic extraction of comments on specific topics from Reddit, while also formatting the text data for direct analysis. The "electric vehicle" filter was applied to gather relevant data. The population of the study consists of user comments from the Reddit platform, while the sample includes comments collected from user discussions on Reddit through the application. The data was collected in January 2025, with the oldest post dating back to February 19, 2016, and the most recent post-dated January 12, 2025.

4.2. Sentiment Analysis Tool (NRC)

Sentiment analysis plays a crucial role in understanding market dynamics, especially in the context of social media. Social

media platforms reflect the emotional and psychological state of investors, with posts and discussions having the potential to influence the future value of financial assets such as stocks and cryptocurrencies. These platforms allow for the rapid dissemination of emotional reactions, shaping market trends. For instance, a surge in positive social media sentiment can drive a company's stock price upwards as investors react to the collective enthusiasm. Unlike traditional financial data, which is typically reported on a weekly, monthly, or quarterly basis, social media can accelerate market responses by quickly spreading real-time news and opinions. This makes social media a vital tool in measuring real-time market sentiment. Furthermore, the influence of news flows is particularly pronounced in financial markets. Social media amplifies the speed at which news about a particular event or development spreads, enabling investors to adjust their perceptions almost instantaneously. For example, a statement from a company's CEO can immediately alter investor sentiment, leading to swift price movements in the stock market. Thus, social media has become a powerful force in shaping market responses, providing a more immediate and reactive view of market sentiment compared to traditional financial reporting methods.

In the initial phase of this research, the study aims to explore the relationship between consumer perceptions and emotional tendencies by analyzing Reddit discussions on EVs. To conduct sentiment analysis, we employ the NRC (National Research Council) sentiment lexicon, a widely recognized lexicon-based approach for identifying emotions in textual data. This method enables a structured evaluation of sentiment by categorizing words into predefined emotional groups. Specifically, the NRC lexicon is built on Plutchik's emotion model, which classifies emotions into eight fundamental categories: Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust. The NRC lexicon also maps words and phrases to specific emotions, enabling a comprehensive analysis of the emotional patterns found in Reddit comments.

Using this approach, this study systematically tracks shifts in emotional sentiment over time, capturing fluctuations in consumer attitudes toward EVs. The integration of lexicon-based sentiment analysis with social media data provides a robust framework for understanding how emotional responses influence consumer behavior and market sentiment. Furthermore, by leveraging a large-scale dataset from Reddit, this analysis enhances the depth and reliability of sentiment measurement, offering insights into how consumer emotions evolve in response to key developments in the EV industry. This comprehensive approach not only strengthens the validity of sentiment analysis but also provides a valuable foundation for subsequent econometric modeling.

4.3. Data Cleaning and Preprocessing

During the research process, an extensive data cleaning and preprocessing phase was implemented to ensure that the collected data was suitable for analysis. The first step involved removing unnecessary elements such as HTML tags, special symbols, and extraneous characters that did not contribute to the semantic structure of the text. Following this, the comments were tokenized into individual sentences, breaking them down into a structured format that facilitated further analysis. To enhance data quality,

stopwords like common words that carry little semantic weight, were systematically removed along with irrelevant components such as emojis, URLs, and user mentions. Additionally, redundant and repetitive comments were filtered out to prevent data bias and redundancy. A thorough noise filtering process was applied to eliminate empty, duplicate, or contextually meaningless content, ensuring a cleaner dataset. Once the preprocessing steps were completed, the refined data was standardized and organized in a structured format, such as CSV or Excel, making it ready for computational analysis. This meticulous preprocessing phase played a crucial role in transforming unstructured raw text into a well-structured dataset, optimizing it for sentiment analysis and econometric modeling in later stages of the study.

After completing the preprocessing phase, the refined dataset was ready for textual analysis. To gain an initial insight into the most frequently occurring words and their relative prominence, a word cloud visualization was generated. This approach helps to identify dominant themes, commonly used terms, and potential trends in user discussions, offering a preliminary understanding of the sentiment landscape before conducting further quantitative analysis.

4.4. Word Cloud

Figure 4. Shows the most frequently used words based on data collected from Reddit. EV and the technologies associated with them play a significant role in environmental sustainability, energy efficiency, and the development of alternatives to fossil fuels. The words *car*, *electric*, *battery*, *EV*, *charging*, *vehicles*, *batteries* and *charging* in the word cloud reflect the key components of this transformation. The increase in the use of electric vehicles aligns with advancements in battery technology and the development of charging infrastructure. Terms like *battery*, *EV* and *charging* serve as proxies for the technological developments necessary for making electric vehicles more efficient and accessible.

These advancements have the potential to transform the automotive industry and represent a significant step toward achieving environmental sustainability goals. The widespread adoption of electric vehicles promises to reduce fossil fuel consumption and

lower carbon emissions. In this context, terms such as *gas*, *oil*, *fuel* and *energy* demonstrate the capacity of electric vehicles to offer environmentally friendly alternatives. The rising popularity of electric vehicles is linked not only to technological advancements but also to societal and economic changes. Words like *people*, *need*, *make*, *want*, *buy* and *still* explain the growing demand for electric vehicles and how this demand is being met by society. Electric vehicles are being preferred as an environmentally friendly, cost-effective, and long-term transportation alternative. Terms like *Tesla*, *China* and *market* point to the significant global players in this field and their impact on market dynamics. Tesla's leadership in the sector and China's role in electric vehicle production are strongly represented by these terms. Additionally, words like *new*, *long*, *miles*, *range* and *mileage* emphasize the range advantages of these vehicles and the innovative solutions they bring to the market. This transformation affects not only consumer demand but also government policies and the strategies of automotive manufacturers.

The environmental benefits of electric vehicles are based on their potential to reduce carbon emissions by consuming less *gas*, *oil* and *fuel* compared to fossil fuel-powered vehicles. Terms like *energy*, *power*, *range*, *vehicles* and *electricity* highlight the energy efficiency and driving range that electric vehicles offer. These vehicles aim to reduce dependence on fossil fuels and create an environmentally friendly transportation model using clean energy. Words like *battery* and *power* symbolize the high energy efficiency of electric vehicles, resulting in lower carbon emissions compared to traditional internal combustion engines. Expressions like *China*, *market*, *vehicle*, *charging*, *government*, and *infrastructure* represent the strategic decisions that drive and shape developments in this sector. Electric vehicles are seen as an important tool in the fight against global warming. The adoption of electric vehicles has the potential to reduce fossil fuel consumption and lower carbon emissions, making it a crucial step toward achieving environmental protection goals.

4.5. Construction of Sentiment Indexes

This study aims to examine the impact of emotional tendencies expressed in Reddit comments on fluctuations in sector indexes related to EVs through sentiment analysis. By analyzing large-

Figure 4: Word cloud

scale user-generated content, the research explores how positive and negative sentiments influence financial trends and market dynamics within the EV industry. In this phase of the study, sentiment scores obtained from Reddit comments are utilized to construct two distinct sentiment indexes: The Negative Sentiment Score (NSS) Index and the Positive Sentiment Score (PSS) Index. These indexes are developed using the Principal Component Analysis (PCA) method, which helps capture the underlying structure of sentiment variations in a statistically meaningful way. The purpose of constructing these indexes is to assess their explanatory power in relation to the performance of the EV sector.

Specifically, the PSS Index is examined to understand its correlation with increased demand, investor confidence, and potential market growth, while the NSS Index is analyzed to evaluate its association with heightened market volatility, risk perception, and potential downturns in sectoral performance. By integrating sentiment analysis with financial modeling, this study provides a deeper understanding of the role consumer emotions play in shaping stock market behavior and investment decisions in the EV sector. These insights contribute to the broader discussion on the predictive power of social media sentiment in financial markets, offering valuable implications for investors, policymakers, and industry stakeholders.

4.6. EV Sectoral Index Data
To examine the explanatory power of sentiment scores obtained through sentiment analysis on comments from the Reddit social media platform in relation to fluctuations in various electric vehicle sector indexes, a quantile regression analysis was performed on daily data from June 1, 2021, to October 31, 2024, depending on the availability of the data. The variables used in this analysis are defined in Table 2.

Three different indexes with high representational power in the electric vehicle sector are used. The index data considered are the EV Index, the AV Index, and the US-China EV Index, which are part of the S&P Dow Jones indexes under S&P Global. These indexes encompass major players in the electric vehicle sector. They include large American companies such as Tesla, as well as key manufacturers based in China and Europe. These indexes also represent the largest electric vehicle markets in the world, including the U.S. and China. Given the weight of these two countries in EV production, these indexes have been chosen. The companies traded in these indexes and their weightings by country are shown in Table 3.

Based on the sentiment scores obtained from NRC, scores related to the emotions of anger, fear, disgust, and sadness are used to form the Negative Sentiment Index (NSS), and scores related to the emotions of anticipation, joy, surprise, and trust are used to form the Positive Sentiment Index (PSS) through PCA analysis.

5. RESULTS

5.1. Sentiment Analysis Results
In the graph in Figure 5, the changes in NRC sentiment intensity from 2016 to 2024 are presented in detail. The distribution among various emotions (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust) reflects the emotional reactions in user comments during specific periods, providing valuable insights into the underlying causes of fluctuations in social media discussions.

In Reddit comments related to electric vehicles, particularly positive emotions such as *joy* and *trust* have shown a significant increase between 2019 and 2024. By 2022, these emotions had seen notable growth; for example, the values for joy and trust reached 2600

**Table 2: Definations and sources of variables for quantile regression**

Variablne	Description	Source
EV	SP Kensho index for electric vehicles.	S&P Dow Jones index
AV	SP Kensho index for autonomous vehicles.	S&P Dow Jones index
US-China EV	SP Index for U.S. and China electric vehicles	S&P Dow Jones index
NSS	Negative sentiment score index (anger, fear, disgust and sadness)	Autors' construction
PSS	Positive sentiment score index (anticipation, joy, surprise, trust)	Autors's construction

Table 3: Country breakdown of sectoral indexes

Country	EV Index		AV Index		US-China EV Index		
	Number of constituents	Index weight (%)	Number of constituents	Index weight (%)	Num. of constituents	Index weight (%)	Top 10 constituents by index weight
United States	27	72.3	18	72.9	16	42.9	Tesla
China	3	8.5	5	20.1	35	57.1	Contemporary Amperex Technology
Japan	2	5.5	1	3.9			BYD (01211)
Italy	1	2.0	1	3.1			TE Connectivity
Canada	1	3.7					BYD (002594)
Vietnam	1	3.3					Luxshare
Sweden	1	2.7					Seres
Luxembourg	1	2.0					Li Auto
							Zhongji
							Aptiv

Source: S&P Dow Jones (2025)

Figure 5: NRC sentiment analysis
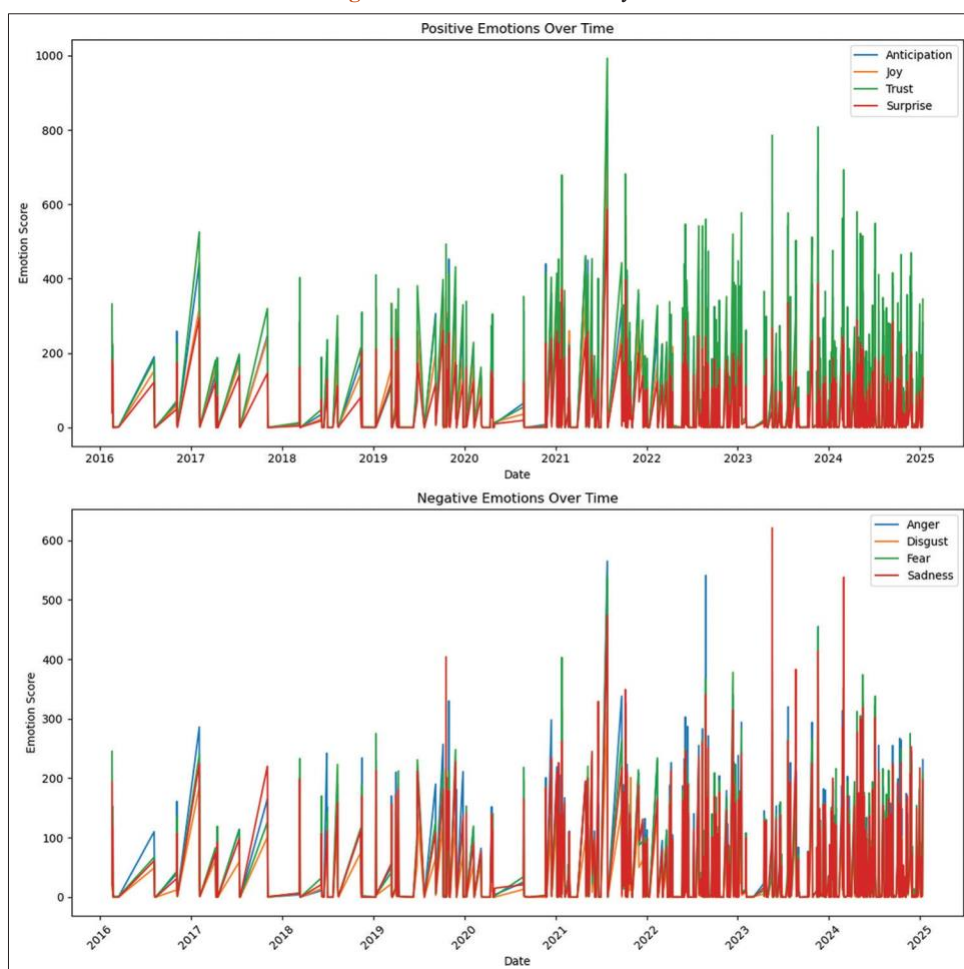
and 1108, respectively, in June 2022. This increase indicates that the societal acceptance of electric vehicles has risen, with greater emphasis on their environmentally friendly features, and that developments in the industry have had a positive impact on users. The growing adoption of electric vehicles, increased user experiences, and heightened societal awareness have reinforced the sense of trust. The rise in trust also highlights that users' confidence in these new technologies has increased, and positive emotions generally align with this confidence. This trend suggests that users view the vehicles' environmental contributions, design, and performance positively.

On the other hand, the fluctuations of negative emotions such as *anger*, *fear* and *disgust* are another noteworthy aspect. These emotions are particularly associated with challenges in 2020, such as the lack of charging infrastructure, supply chain issues, and increased battery costs. For instance, the anger value peaked in 2020 (June 2020: 291), reflecting users' frustrations regarding vehicle accessibility, pricing, and service availability. However, these negative emotions generally decreased over time, giving way to more neutral or positive emotions. This could indicate that infrastructure issues were being addressed and users' confidence in the technology was growing.

The fluctuations observed in sentiment analysis regarding electric vehicles have aligned with developments in the industry. Advancements in electric vehicle technology and sector innovations have led to significant changes in users' emotional tendencies. Positive factors such as technological innovations and improved battery efficiency have increased user excitement, which has contributed to rising emotions such as anticipation and joy. Positive expectations about the future of electric vehicles, along with improving infrastructure, have fostered more trust among users and enhanced the societal perception of electric vehicles.

5.2. Quantile Regression Analysis Results

In this part of the study, time series quantile regression analysis, conducted with daily data between June 1, 2021, and October 31, 2024, reveals the relationships between positive and negative sentiment indexes (NSS and PSS) and electric vehicle sector indexes (EV, AV, and US-China EV).

Descriptive statistics for the variables used in the analysis are provided in Table 4. The skewness value indicates whether the distribution of a variable is symmetric. According to this, electric vehicle variables show a highly right-skewed distribution, while the skewness coefficients of the sentiment indexes are lower but positive, indicating that the distribution is more concentrated in the right tail. Kurtosis measures the concentration of extreme values in a distribution. For a normal distribution, the kurtosis value is 3. Accordingly, the electric vehicle indexes show fewer extreme values compared to the normal distribution, while the sentiment

indexes have a higher concentration of extreme values. On the other hand, the Jarque-Bera (JB) test is a statistical test used to check if a distribution follows a normal distribution. According to the JB statistic, it is concluded that none of the series follow a normal distribution.

The BDS (Brock-Dechert-Scheinkman, 1987) test results are used to determine whether a time series is independently and identically distributed. Determining whether a time series is linear using the BDS test is a critical step in selecting the appropriate model, improving forecasting accuracy, and making more precise market analyses. In datasets that exhibit complex and nonlinear structures, such as financial time series, the BDS test helps assess whether classical methods may be insufficient.

In Table 5, the BDS test results for different embedding dimensions are presented for the EV Index, AV Index, US-China EV Index, NSS index and PSS index series.

The BDS test statistics for the EV Index, AV Index, and US-China EV Index are quite high and significant at the 1% level. This indicates that these series do not follow identically distributed (IID) process. As the embedding dimension increases (from 2 to 6), the value of the test statistics increases, suggesting that non-linear structures become more prominent in these series. This strongly emphasizes that these series contain non-linear complex structures. For NSS and PSS, the BDS test statistics are relatively lower and only significant in some

embedding dimensions. This indicates that these series also contain non-linear structures. The JB and BDS tests confirm that quantile regression model is suitable to produce consistent results.

The ADF (Augmented Dickey-Fuller) unit root test results are used to determine whether a time series is stationary. The use of quantile regression requires the series to be stationary at the level. The results of the ADF unit root test are presented in Table 6. According to these results, all variables are stationary at different significance levels.

The quantile regression model proposed by Koenker and Bassett (1978) offers a more flexible structure compared to the Ordinary Least Squares (OLS) regression model. The quantile regression model takes into account the outliers in the series and allows for the examination of relationships between variables at all points of the conditional distribution of the dependent variable. Quantile regression is considered a more advanced method for understanding market dynamics compared to traditional regression models. While classical regression techniques primarily focus on capturing the average relationship between variables, they often overlook important variations that exist at different points in the distribution of the data. Quantile regression, on the other hand, allows for a more effective analysis by examining the relationships at various quantiles, such as the upper or lower percentiles of the market, rather than just the mean. This method is particularly valuable in financial markets, where extreme events or outliers,

Table 4: Descriptive statistics of variables

Descriptive Statistics	EV	AV	US-China EV	NSS	PSS
Mean	218.98	538.1	2181.39	20.74	31.41
Std	78.24	176.7	469.59	56.0	84.54
Min	130.39	320.54	1503.99	0.0	0.0
%25	150.9	394.24	1779.26	0.0	0.0
%50	189.38	452.06	2038.04	0.0	0.0
%75	304.02	741.35	2516.98	1.5	2.25
Max	405.39	923.08	3411.75	472.34	794.17
JB	122.654***	138.176 ***	95.449***	10162.891***	11444.585***
Skewness	694	734	676	3.47	3.508
Kurtosis	−1.005	−1.074	−674	13.965	14.987
Obs.	1003	1003	1003	1003	1003

***, **and □indicate statistical significance at the 1%, 5% and 10%levels, respectively.

Table 5: BDS test results

Variable	EV	AV	US-China EV	NSS	PSS
2	108.93***	109.62***	109.89***	1.273	1.596
3	120.83***	124.42***	119.41***	1.399	1.788*
4	135.95***	143.55***	131.33***	1.602	1.836*
5	157.37***	170.72***	148.23***	1.708*	1.84*
6	186.86***	208.66***	171.18***	2.109**	2.091**

***, **and □indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 6: ADF unit root test results

Variable	EV	AV	US-China EV	NSS	PSS
Test statistic	−1.722**	−1.747**	−2.582***	−6.029***	−7.075***
cv (1%)	−2.337	−2.349	−2.349	−2.337	−2.337
cv (5%)	−1.649	−1.654	−1.654	−1.649	−1.649
cv (10%)	−1.284	−1.287	−1.287	−1.284	−1.284

***, ** and □ indicate statistical significance at the 1%, 5% and 10%levels, respectively. cv: Critical value

such as market crashes or surges, can have significant impacts on asset prices. Capturing these variations across the distribution, quantile regression provides a deeper understanding of how market reactions differ under complex economic conditions and enables a more comprehensive assessment of the relationships between variables.

$$y_t = x_t\alpha(\tau)+\varepsilon(\tau), quantile_\tau(y_t\,|\,x_t) = x_t\alpha(\tau) \qquad (1)$$

In this equation, y_t, represents the electric vehicle index; x_t, is the vector of independent variables (NSS and PSS); $quantile_\tau(y_t\,|\,x_t)$, represents the τ conditional quantile of y given x. τ, denotes the quantile of the regression, where $0<\tau<1$. Three different electric vehicle sector indexes are used in this study, so analyses are conducted according to three different models.

Table 7 shows the analysis results of the relationship between EV and sentiment indexes (NSS and PSS). According to the findings, the coefficients for NSS are negative at all quantiles, and their effects are significant at different levels of significance.

According to the findings in Table 7, it is concluded that negative emotions have an adverse effect on the EV index. The coefficients are negative in all quantiles, and the significance levels vary. As the quantiles increase (from 0.3 to 0.8), the negative effect of NSS rises. However, at the 0.9 quantile, this effect decreases relatively (−0.8729), indicating that different dynamics come into play as we approach the extreme values. On the other hand, the coefficients for the other variable, PSS, are positive across all quantiles, and the significance levels are generally high. This indicates that positive emotion scores have a positive effect on the EV Index. As the quantiles increase (from 0.4 to 0.8), the positive effect of PSS increases. However, at the 0.9 quantile, the coefficient shows a decrease (0.5020).

The findings regarding the effects of negative emotion scores (NSS) and positive emotion scores (PSS) on the AV Index in different quantiles are presented in Table 8. The NSS coefficients are negative in all quantiles, indicating that negative emotion

scores have a detrimental impact on the AV index. During periods when the AV index is high, the negative effect of NSS is observed to increase. On the other hand, the PSS coefficients are generally positive, with the effect of positive emotions significantly increasing in the middle and upper quantiles.

Table 9 shows the effect of the NSS and PSS sentiment indexes on the US-China EV index. According to the findings, the coefficients for NSS are negative across all quantiles. This indicates that negative emotion scores have a consistently adverse impact on the US-China EV index. Although the magnitude of the negative effect varies across quantiles, it is particularly strong in the middle and upper quantiles (0.4-0.8). The coefficients for PSS are mostly positive, but the significance levels vary between quantiles. The magnitude of the positive effect peaks in the middle quantiles (0.4-0.8), and the effects in these quantiles are generally statistically significant.

Based on the findings, when evaluating the results as a whole, the impact of negative emotions (e.g., market fear or anxiety) on the EV market should be considered, and measures should be developed to address these effects. The strong influence of positive emotions may indicate that investors make sentiment-driven decisions.

In all the graphs in Figure 6, it is observed that negative sentiment strongly pulls the market down, especially in the middle and upper quantiles. This may indicate that negative news in financial markets leads to a loss of confidence and risk aversion in investor behavior. Positive sentiment appears to be most effective in the middle quantiles (representing average market performance), but the positive effects are limited at the upper extremes. This suggests that the market is sensitive to positive news and confidence but reaches a saturation point at higher levels.

Sentiment scores derived from Reddit comments can be an effective tool for developing market sentiment-based strategies and understanding investor behavior. The findings of this study suggest that sentiment analysis plays a crucial role, especially

Table 7: Quantile regression results (dependent variable: EV index)

| EV	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
NSS	−0.0488	−0.1319	−0.2801**	−0.5039**	−0.9095***	−1.2559***	−1.3818*	−1.4627***	−0.8729***
PSS	0.0173	0.0558	0.1432	0.2947*	0.5786***	0.7983***	0.8272*	0.8014***	0.5020***

***, **and □indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 8: Quantile regression results (dependent variable: AV index)

AV	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
NSS	−0.1980	−0.0040	−0.3170	−0.5660	−1.5350***	−2.2500*	−3.3560*	−3.3870***	−2.2230***
PSS	0.0660	−0.0620	0.1500	0.2940	0.9970***	1.4090*	1.9450	1.8160***	1.2440***

***, ** and □ indicate statistical significance at the 1%, 5% and 10%levels, respectively

Table 9: Quantile regression results (dependent variable: US-China EV Index)

US-China EV	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
NSS	−0.1818	−0.8053	−1.6368	−3.9903***	−5.7905***	−6.6285***	−6.9802***	−8.1660***	−3.4738*
PSS	−0.0472	0.2205	0.7569	2.4133**	3.6047**	4.0511**	3.9812**	4.6013**	1.8838

***, **and □indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure 6: Quantile regression prediction results
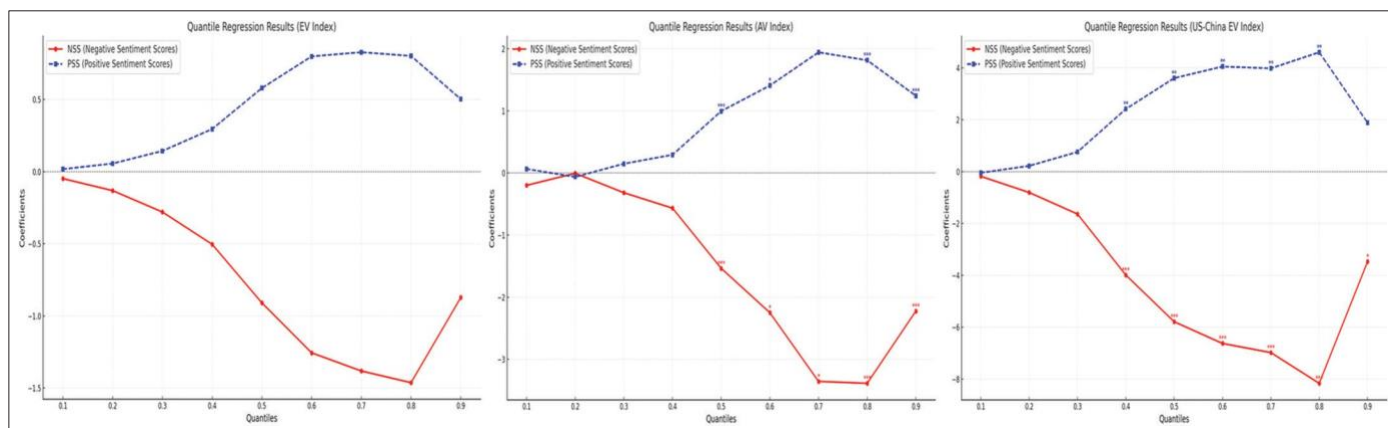
in understanding the decision-making processes and market perceptions of individual investors. Electric vehicle demand can be a leading indicator for sector indexes. If demand is strong, investor confidence increases, and stock prices rise. If demand declines, sector indexes may experience fluctuations or downturns.

The relationship between consumer demand trends and electric vehicle sector index performance has a key role for understanding how shifts in public sentiment influence the broader market. Since sentiment scores derived from social media platforms like Reddit reflect real-time consumer perceptions, they can serve as leading proxy indicators of sector performance. When positive trends on sentiment scores get higher, it means consumers have more confidence about EVs, ofen driven by factors such as technological developments, goverment incetives or improved charging insfrastructure. If demand rises, EV manufacturers and also investors anticipate higher sales and revenue growth and thus these positive trends increase stosk prices of EV companies. This positive market outlook translates into an upward trend in EV sector indexes. However, a rise in negative sentiment score index due to high prices, lack of charging stations and so on can lead to a decrease in consumer demand, lower projected sales and weaker earning expectatitons for EV manufacturers. On the other hand, investors react to this negative outlook by reducing their positions in EV stocks, this causes declining sector indexes. Moreover, increased negative sentiment may also signal regulatory challenges or market distortion, leading to higher volatility in the EV sector index performance.

6. CONCLUSION AND RECOMMENDATIONS

In this study, sentiment analysis is conducted on electric vehicle demand using text mining methods based on comments from the social media platform Reddit, examining its interaction with leading electric vehicle sector indexes. The process begins with data collection from Reddit and progresses through an analytical framework that extends to economic modeling. Initially, web scraping techniques are used to collect comments from Reddit, followed by a pre-processing stage where the data is cleaned and prepared for analysis. Subsequently, sentiment analysis is performed using the NRC sentiment lexicon and sentiment scores

are processed through Principal Component Analysis (PCA) to derive negative and positive sentiment score indexes. After this stage, sectoral index data related to electric vehicle companies' stock market performance is compiled, leading to the economic modeling stage. Finally, a time series quantile regression analysis is applied to estimate the extent to which sentiment indexes derived from comments can explain fluctuations in sectoral indexes. This comprehensive approach integrates text mining with economic modeling, providing valuable insights into the relationship between social media sentiment and financial market trends.

In sentiment analysis, the relationships between positive and negative emotions become more evident during certain periods. While negative emotions have an adverse impact on the market, positive emotions have been found to boost confidence. Furthermore, through quantile regression analysis, the sentiment indexes were found to have different effects on EV sector indexes. It was determined that negative emotions, reflecting market fear or uncertainty, tend to lead to price declines, while positive emotions increase market confidence and drive price fluctuations. These findings provide important data for predicting market trends and trading strategies. Based on the results, negative emotions (particularly fear and anger) have a negative impact on the EV sector, while positive emotions increase market confidence and amplify price volatility. These findings suggest that sentiment scores could be an effective tool in estimating consumer demand and a leading indicator for sector indexes. The analysis in this study indicates that sentiment scores derived from Reddit play a significant role in understanding the fluctuations in the EV sector indexes.

The results could provide insights into predicting consumer demand trends, forecasting purchasing behavior fluctuations, supporting marketing strategies and enhancing supply chain management. Assuming that social media platforms like Reddit reflect consumers' real-time thoughts and emotions, an increase in positive sentiment scores typically signals rising consumer interest and confidence in electric vehicles, which may lead to higher sales. Conversely, a rise in negative sentiment scores could indicate concerns or dissatisfaction among consumers, suggesting a potential decline in demand. Products or brands that are heavily discussed on Reddit may often experience short-term shifts in consumer interest and purchasing behavior. Therefore, sentiment

scores can serve as an early warning system to predict trends in consumer demand. Additionally, sentiment scores can be used as inputs in marketing and sales forecasting models. Specifically, sentiment analysis-based demand prediction strategies can help identify periods of increasing or decreasing interest in electric vehicles. A rise in negative sentiment scores could signal potential barriers to adoption, prompting businesses to adjust their strategies to address consumer concerns and improve market acceptance.

This study provides important implications for both financial analysts and policymakers. The findings suggest that tracking sentiment scores could help investors make more informed decisions regarding EV stocks. Integrating sentiment analysis into investment strategies enables traders and fund managers to more effectively predict market fluctuations influenced by changes in consumer sentiment. Moreover, sentiment-based trading strategies could enhance portfolio diversification by considering the emotional tendencies of the market. From a business and marketing perspective, EV manufacturers can leverage sentiment analysis to gauge consumer preferences and concerns. This study highlights the potential for businesses to use real-time sentiment tracking as an early warning system to identify shifts in demand, allowing them to adjust their production and marketing strategies accordingly. Additionally, automakers and policymakers can use sentiment indexes to improve consumer engagement, develop incentive programs and address widespread concerns regarding charging infrastructure, range anxiety and cost barriers.

The uniqueness of this study lies in its focus on examining the relationship between various indexes related to the EV sector using sentiment analysis results from Reddit. By using sentiment scores to evaluate relationships between sector indexes, quantile regression analysis has been performed. This method offers a more in-depth evaluation compared to previous studies, as it converts features extracted through text mining into quantitative analysis. One of the key methodological contributions of this research is its application of a hybrid approach that combines text mining with econometric modeling. Unlike prior studies that rely on structured economic indicators, this study provides a novel way of incorporating unstructured social media data into econometric analysis. This integration allows for a deeper understanding of consumer sentiment and its implications for financial markets.

This study also draws attention to the growing importance of social media as a powerful tool for measuring market sentiment, complementing traditional financial indicators. Social media platforms provide real-time emotional and psychological insights, quickly disseminating investor sentiment that influences market dynamics. In the EV sector, where market conditions and consumer behavior are rapidly evolving, social media sentiment allows investors to respond to shifts in sentiment more promptly. Unlike traditional models that focus on average market behavior, this study demonstrates how social media sentiment can capture the tail effects of the market, offering valuable insights for predicting market fluctuations and making more informed investment decisions. Furthermore, the study underscores the critical connection between the electric vehicle sector and sustainable investments, as EVs play a pivotal role in achieving environmental sustainability goals by reducing carbon emissions. The sector is

not only a sustainable alternative but also a key player in green finance, with the adoption of green bonds, sustainability-linked financing, and Environmental, Social, Governance (ESG) criteria driving investment. Government incentives further accelerate this transition, attracting sustainable investors and bolstering market confidence in the EV sector. This research emphasizes that EV stocks are integral to both financial and environmental sustainability, offering unique insights into how social media sentiment can help forecast sector performance, thus aiding in the broader goal of transitioning to a low-carbon economy.

However, the study has some limitations. First, it exclusively relies on Reddit data, which may not fully represent the broader consumer base. Future studies could integrate data from multiple social media platforms, such as Twitter, Facebook, and online forums, to provide a more holistic perspective. Additionally, expanding the dataset to include a more extended time period could help capture long-term sentiment trends. A comparison between emotional data and country-specific economic indicators could be explored. Another avenue for future research could explore the demographic characteristics of social media users and how different consumer segments react to EV-related developments. Investigating sentiment shifts during major industry events, such as regulatory changes, technological breakthroughs, or supply chain disruptions, would also provide valuable insights. Future research should build upon these insights by expanding the dataset, refining sentiment analysis techniques, and exploring the broader implications of sentiment-driven market movements.

7. FUNDING DECLARATION

8. ETHICAL APPROVAL STATEMENT

The data used in this study were collected from the Reddit platform using an archival research method, which does not involve direct interaction with human participants. As the data were obtained from publicly accessible social media comments, ethical approval in accordance with the Declaration of Helsinki was not required. The study adhered to ethical standards by ensuring participant anonymity and using publicly available data.

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