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Is the U.S. energy independence and Security Act of 2022 associated with stock market volatility?

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ABSTRACT

This study investigates the influence of the U.S. Energy Independence and Security Act (EISA) of 2022 on stock market volatility. Considering potential policy impacts on market dynamics, it employs a mean-reverting jump-diffusion model for volatility analysis, supported by rigorous hypothesis testing to validate empirical findings. For investor sentiment analysis, a pre-trained model (BERT-base-multilingual-uncased) is used to assess sentiment, with logistic regression and Bidirectional LSTM utilized for sentiment prediction. Contrary to conventional findings, logistic regression outperforms Bidirectional LSTM for the small dataset. Overall, the study estimates show no statistically noteworthy difference in volatility before and after implementing the EISA of 2022. This study provides valuable insights for navigating financial decisions within the intricate landscape of energy markets.

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1. Introduction

The energy landscape in the United States (US) and globally is undergoing a rapid transformation marked by a notable shift from coal to renewable energy sources and natural gas (Maiti, 2022a, 2022b). As a cornerstone of contemporary societal and economic progress, energy remains critical (Cifuentes-Faura et al., 2024). Despite this shift, traditional fossil fuels comprising oil, heating oil, gasoline, and natural gas still contribute over 80% to global energy consumption, exerting a profound impact on the world economy. The enactment of the EISA in 2022 marks a significant milestone, addressing US energy independence, oil and natural gas production, and importation. This legislation mandates a plan for the US to achieve energy independence by 2024 and assigns the US Department of Energy (DOE) responsible for creating a program and issuing regulations to ensure the nation becomes a net energy exporter.

Major events can substantially impact the sentiments of both investors and consumers (Jeong et al., 2023; Khan et al., 2023) and the overall market landscape (Cai et al., 2020). Investor sentiment is pivotal in these markets, and noteworthy events can sway sentiment, influencing energy markets (Chen et al., 2023). Given these ongoing changes, comprehending energy market volatility assumes paramount importance. The surge in energy stocks further underscores the need for traders to effectively model this volatility (Chen et al., 2023; Kocaarslan and Soytas, 2021; Jebabli et al., 2022). Recent studies in US energy markets underscore the dynamic spillovers among geopolitical risk, climate risk, and energy markets from an international perspective (Jin et al., 2023). The study by Karkowska and Urjasz (2023) contributes by examining volatility spillovers between dirty and clean energy markets and global stock indices, especially during periods of heightened geopolitical risk, such as the unexpected Russian invasion of Ukraine. Moreover, the study by Lorente et al. (2023) delves into the interconnectedness between the climate change index, green financial assets, renewable energy markets, and the geopolitical risk index. Collectively, these studies affirm the correlation between geopolitical risks and volatility in the energy market.

This study stands out by applying a unique jump-diffusion model, a departure from its traditional use in option pricing (Nomikos and Soldatos, 2010). Unlike the complex construction of the likelihood function employed in conventional maximum likelihood estimation, as demonstrated by the Merton jump-diffusion model, the Nelder-Mead-based optimization method avoids such intricacies (Özdemir, 2019). The

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study addresses the limitations of standard maximum likelihood procedures in estimating jump-diffusion models for asymmetric jump-diffusion models (Ramezani and Zeng (1998); Honore, 1998). In sentiment analysis, BERT-based multilingual-uncased-sentiment scores are used to offer comprehensive insights. This study innovatively employs simple jump-diffusion models for straightforward volatility analysis. It utilizes Nelder-Mead-based optimization to estimate parameters, deviating from conventional Maximum Likelihood Estimation (MLE).

Additionally, the study presents sentiment scores alongside standard predictions and highlights changes in Twitter ("X") data collection methods. Additionally, this study offers several valuable contributions to the existing literature. It focuses on the recent and underexplored EISA of 2022, providing new insights into its effects. The study demonstrates the causal impact of this legislative change on market volatility through a pre and post-comparison, highlighting its influence on market dynamics. Primarily addressing energy market volatility, the findings are helpful for risk management. Furthermore, the study employs advanced techniques to promote a data-driven decision-making approach to understanding market behavior. Overall, the findings are instrumental in evaluating the effectiveness of the policy.

Thus, the present study is valuable in the context of climate change and energy transitions, given the significant policy shifts in the EISA of 2022. This legislation directly impacts the energy sector by influencing consumer prices and production costs. Understanding energy market volatility is crucial for minimizing overall risks and effective portfolio management. Insights into the impact of legislation on energy market volatility are beneficial to both investors and analysts. Moreover, maintaining stable market conditions is essential for gaining public confidence, as energy market volatility can directly affect public sentiment regarding costs. Lastly, this study significantly contributes to the existing literature on energy economics and market dynamics, making it valuable to audiences focused on the energy sector.

The subsequent sections of this study are organized as follows: Section 2 provides a comprehensive Literature Review, Section 3 details the Data used in the analysis, Section 4 outlines the employed Methods, Section 5 presents the Findings, Section 6 engages in Discussions, and the study concludes with Section 7, offering insights and implications.

2. Literature Review

The dynamic landscape of the energy market in the US necessitates a nuanced exploration of factors influencing financial decisions within this sector. In this section, we critically examine existing studies to elucidate the role of investor sentiment, energy market volatility, and regulatory frameworks in shaping financial decisions within the US energy market.

2.1. Investor sentiment in energy markets

Investor sentiment, a key driver of financial markets, holds particular significance in the energy sector. Many studies (such as Assaf et al., 2021; Du et al., 2016; Jeong et al., 2023; Quadan and Nama, 2018) emphasize the substantial influence of public sentiment on energy markets, indicating that major events significantly impact the sentiments of both investors and consumers. This sentiment, in turn, shapes the overall energy market landscape (Assaf et al., 2021; Cai et al., 2020; Zhu et al., 2020). Research conducted by Chen et al. (2021a,b), Kocaarslan and Soytas (2021), and Jebabli et al. (2022) highlight the influence of investor sentiment on energy stocks, underscoring the imperative for traders to adeptly model and navigate the ensuing volatility. Recognizing the pivotal role of investor sentiment becomes imperative for interpreting market behaviors and making well-informed financial decisions.

2.2. Sentiment analysis in microblogging domains

An extensive body of literature has systematically examined sentiment analysis within microblogging domains, with Pang et al. (2008) presenting a thorough survey encompassing various studies in this domain. The investigation into the influence of microblogging on brand perception has been a subject of scholarly scrutiny, as exemplified by the work of Jansen et al. (2009). Twitter has prominently emerged as a pivotal platform for conducting sentiment analysis, as underscored by studies such as that of Muhammad et al. (2023), wherein Twitter data are employed to discern sentiments across 14 African languages. Furthermore, Nezhad & Deihimi (2022) leveraged Twitter data to conduct a nuanced sentiment analysis on importing COVID-19 vaccines in Iran. Complementary to this, the study by Manguri et al. (2020) meticulously examined sentiment patterns surrounding the COVID-19 outbreak by analysing Twitter hashtag data. This collective body of research contributes substantively to our understanding of sentiment dynamics within the context of microblogging platforms, notably Twitter, and their multifaceted applications in diverse fields.

2.3. Energy market volatility

Given the ongoing transformation in the energy landscape, comprehending energy market volatility is paramount. The surge in energy stocks underscores the need for advanced modeling of volatility (Chen et al., 2023; Jebabli et al., 2022; Halkos and Tsirivis, 2019; Ma et al., 2023a). The study by Jin et al. (2023) further extends this understanding by highlighting dynamic spillovers among geopolitical risk, climate risk, and energy markets on an international scale. Similar thoughts were reflected in other recent studies (Gu et al., 2023; Ma et al., 2023b; Li et al., 2023; Zhu et al., 2023). Further, Liu et al. (2022), Karkowska and Urjasz (2023), and Tan et al. (2021) contribute by examining volatility spillovers between dirty and clean energy markets, emphasizing the interconnectedness of global stock indices during periods of heightened geopolitical risk. Lorente et al. (2023) also explore the relationships between the climate change index, green financial assets, renewable energy markets, and the geopolitical risk index. Their findings and other studies confirm the link between geopolitical risks and energy market volatility, emphasizing the need for a comprehensive analysis of these interrelationships. Furthermore, various forms of sentiment uniquely affect volatility within the energy market. For instance, Quadan and Nama, 2018 demonstrated how investor sentiment, captured by several proxies, influences oil prices and volatility. Similarly, Song et al. (2019) utilized investment sentiment derived from Google search indices to illustrate its impact on the renewable energy sector. In a comprehensive investigation, Chen et al. (2021a,b) established connections between different types of sentiment and energy market volatility. Additionally, cross-market investor sentiment based on various types of energy futures has been found to impact energy market volatility (Chen et al., 2022). Numerous other studies have corroborated the significant role of sentiments in influencing energy market volatility (Assaf et al., 2021; Jawadi et al., 2024; Shen et al., 2023).

2.4. Regulatory frameworks and financial decisions

The enactment of the EISA in2022[1] adds a regulatory dimension to exploring financial decisions in the US energy market. This landmark legislation mandates a plan for the US to achieve energy independence by 2024 and assigns the DOE to create a program and issue regulations to ensure the nation becomes a net energy exporter. The regulatory framework introduces a structured approach to energy market activities, impacting financial decisions and market dynamics. Understanding the

[1] Details of the act can be accessed at https://www.energy.senate.gov/services/files/92E7EAA5-E7BC-48E1-8E7F-FE688AE43252.

implications of this regulatory landscape is crucial for stakeholders navigating the evolving energy market.

2.5. Innovative modeling approaches

Numerous studies have extensively explored energy volatility modelling, particularly for electricity prices (Maiti, 2022c; Maiti et al., 2023), emphasizing the incorporation of jumps and stochastic volatility in the modelling process (Kaminski, 1997). The limitations of conventional models, such as geometric Brownian motion and mean-reverting processes, in capturing electricity spot prices have been identified by Barz and Johnson (1998). Deng (2000) proposed three mean-reverting jump-diffusion stochastic models in response, introducing a transform function for energy commodity price estimation. Various jump-diffusion models have evolved, addressing volatility and option pricing for diverse assets. Notably, Feng and Linetsky (2008) established a jump-diffusion process tailored for stocks and derived corresponding option pricing methodologies. Balajewicz and Toivanen (2017) also extended this exploration by applying Merton, Heston, and Bates jump-diffusion models, comprehensively capturing volatility and price dynamics within American and European options.

Recent research builds on this extensive literature to introduce innovative modelling approaches in the form of the jump-diffusion model for analyzing volatility in financial markets (Nomikos and Soldatos, 2010; Özdemir, 2019). The present study distinguishes itself by applying a unique jump-diffusion model, departing from its conventional usage in option pricing. The chosen Nelder-Mead-based optimization method streamlines parameter estimation and effectively addresses the limitations associated with standard maximum likelihood procedures, as discussed in prior literature (Ramezani and Zeng, 1998; Honore, 1998). Furthermore, this study incorporates sentiment analysis through BERT-base-multilingual-uncased, offering comprehensive insights into prevailing sentiments influencing financial decision-making. Along with exploring changes in Twitter data collection methods, integrating sentiment scores with conventional predictions represents notable methodological innovations within the scope of this study. This research contributes to a nuanced understanding of energy market dynamics, integrating traditional modelling techniques with innovative approaches to offer a holistic perspective on financial decision-making processes within this critical sector. More prominently, our work sets itself apart with an innovative modelling approach in two distinct ways. (i) Stochastic Modelling: Stochastic modelling is widely employed in option pricing, necessitating rigorous mathematical computations and assumptions regarding the distribution of stock prices. Through MLE, optimal drift and volatility terms are derived, ensuring the maintenance of stock prices. We propose an alternative approach that eschews assumptions regarding the underlying stock process. Our method facilitates straightforward yet effective stock price simulation by introducing a simple augmentation to Brownian motion. Empirical validation demonstrates that simulated prices exhibit positivity and adhere to observed market patterns; (ii) Sentiment Analysis: Traditionally, sentiment analysis involves binary classification of tweets as positive or negative, gauging their influence on investor decisions within specific time frames. Our research extends this paradigm by scoring sentiments over prolonged periods, capturing the overall investor sentiment toward the US energy market pre and post-policy implementation. We evaluate sentiment shifts within the US energy market by leveraging a pre-trained neural network model renowned for its text classification proficiency. This methodology is validated using a small dataset, leveraging the effectiveness of neural networks in text classification. Overall, this section establishes a foundation for the subsequent sections by examining the interplay of investor sentiment, energy market volatility, and regulatory frameworks in shaping financial decisions within the US energy market. The synthesis of existing studies informs the innovative approach undertaken in this study, contributing to a deeper understanding of the factors influencing financial dynamics in this critical energy sector.

3. Data

3.1. Data source

This study utilizes two distinct data sources. The first encompasses a time series dataset of the S&P 500 Energy Index, serving as a proxy for the US energy markets and sourced from Yahoo Finance. The S&P 500 index, widely acknowledged as a proxy for the US equity market, has been frequently employed in previous research and used as a benchmark for the US stock market (Olson et al., 2014; Benkraiem et al., 2018). The second source comprises text data extracted from Twitter tweets, a platform researchers frequently use for sentiment analysis. Given its users' ability to share thoughts and opinions, Twitter proves invaluable for sentiment analysis (Giachanou and Crestani, 2016; Zimbra et al., 2018; Sarlan et al., 2014).

3.2. Data descriptions

Table 1(a) describes the data used for this study. The time series data for the stochastic modeling was sourced from Yahoo Finance using web scraping or retrieval methods. The two-year period includes 504 observations, corresponding to the 252 trading days per year. The Twitter data was manually collected from the Twitter archive using time filters and the hashtag #USEnergyMarkets, ensuring at least one tweet per day. Consequently, the data points exceed 365 per year, as more than one tweet was sometimes included based on relevance. Both datasets cover the same time frame.

3.2.1. S&P energy index

The continuous dataset of adjusted closing prices for the S&P Energy Index spans from February 1, 2021, to February 1, 2023, with a daily frequency, resulting in approximately 504 observations (see Fig. 1). This timeframe was selected to scrutinize the impact of the EISA of 2022, effective from February 2022. The objective is to evaluate the effects of this policy on energy market volatility before and after its implementation. Notably, the average returns of the S&P Energy Index improved post-policy, evident from the mean value in Table 1(b). However, the volatility, indicated by the standard deviation of the index, exhibited no significant change pre and post-policy (Table 1(b)).

3.2.2. Twitter data

Tweets about the US energy markets were gathered for the corresponding period, spanning from February 1, 2021, to February 1, 2023. This collection aimed to scrutinize the influence of the policy on investor sentiments within the energy markets. An average of 33 tweets per month was amassed during this timeframe, culminating in 800 observations over the two years. For further research, the Twitter data can be acquired for replication in two ways. One method is manual collection, where tweets are read and gathered as we have done. The other method uses the Twitter Application Programming Interface (API), which requires paying premium costs to obtain data for the same timeframe. The reasons for these approaches are discussed below in the data limitations section.

Table 1a
Data descriptions.

	S & P Energy Index	Twitter Data
Data Source	Yahoo Finance	Twitter
Frequency	Daily	Daily
Type	Time series data	Daily Tweet Archive
Data Collection Method	Web Scrapping	Manual Data Collection
Time Frame	01-02-2021 to 01-02-2023	01-02-2021 to 01-02-2023
Observations	504	800

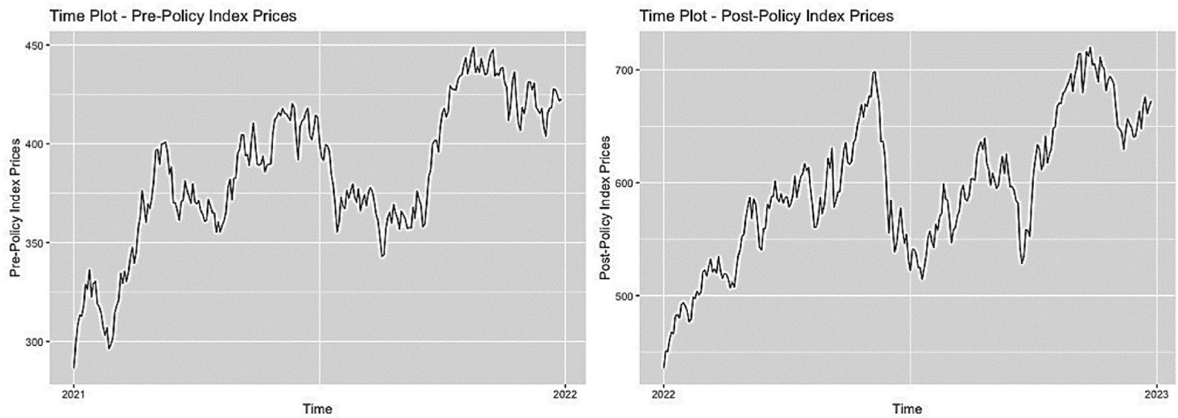

Fig. 1. Spot price.

Table 1b
Summary statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Pre-Policy Prices	251.0	401.11	56.50	286.5	696.69
Post-Policy Prices	247.0	605.66	61.58	435.83	720.16

3.2.3. Data collection limitations

Twitter offers an API for tweet collection, as detailed by Wisdom and Gupta (2016). However, this method is limited to retrieving data from the past seven days. Accessing tweets older than seven days requires a premium account, which can cost hundreds of dollars, as Feizollah et al. (2019) reported. Several open-source APIs have been developed to address this limitation, such as SNSCRAPE (Bernal et al., 2021) and Twint, an advanced Python scraping tool for Tweets from Twitter profiles (Bhakuni et al., 2022). These alternatives are explored, but their reliability decreased following Twitter's acquisition by Elon Musk and subsequent security enhancements. Other open-source APIs have also been tested but have failed to bypass the heightened security measures. Consequently, we resorted to manual data collection and entry into Excel. This approach ensures data reliability with minimal cleaning required. Despite the availability of data for the S&P Energy Index from 2007 onwards on Yahoo Finance, we collected data for the same timeframe to maintain consistency with the Twitter data. Unfortunately, volatility data for the S&P Energy Index was unavailable, which would have been valuable for volatility modeling.

4. Methods

The S&P Energy Index data formed the basis for optimizing a simple mean-reverting jump-diffusion model to determine its parameters. Subsequently, short-term, and long-term volatility metrics were calculated for discrete time intervals. Simultaneously, Twitter data underwent preprocessing and was utilized to assess sentiment using a BERT transformer neural network, facilitating the calculation of sentiment scores.

4.1. Mean-Reverting Jump Diffusion Model

Models integrating jumps and stochastic volatility have demonstrated significant effectiveness in capturing price dynamics in non-storable commodities, particularly energy commodities (Deng, 2000). Deng's research explores various models tailored for pricing derivatives linked to energy commodities. In this study, a simple mean-reverting jump-diffusion model, akin to the Merton jump-diffusion model, is employed to analyze volatility before and after policy changes. The mean-reverting jump-diffusion model extends from Brownian Motion, recognized as one of the most effective processes for modeling stock prices (Areerak, 2014). The Brownian motion used for simulation is expressed in Eq. (1).

$$S_{j+1} = S_j * \left(1 + \mu\ \Delta t + \sigma * \Delta W_j\right) \tag{1}$$

where j = 1, 2, 3, …, N, and N is the number of days to be simulated; S_{j+1}, S_j are the stock price at time j and j+1; μ Δt: The drift term, accounting for the expected growth rate of the stock price and representing the average return per unit of time; $\Delta t = 1/252$; $\sigma * \Delta W_j$: the volatility term, capturing the random fluctuations in the stock price, where $\Delta Wj = Zj\sqrt{\Delta t}$, The random variable Zj is the standard normally distributed random variable with mean = 0 and variance = 1.

The objective is to assess the impact of the EISA of 2022 on energy price volatility. Energy prices typically fluctuate around values influenced by factors such as the marginal cost of electricity generation and demand levels, showing a tendency for mean reversion towards an equilibrium price. However, due to the non-storability of electricity, short-term supply-demand imbalances cannot be mitigated through inventory adjustments, leading to increased volatility. Supply-side disruptions, such as generation or transmission constraints and unexpected outages, can trigger short-lived price spikes as the market adjusts to capacity limits (Nomikos and Soldatos, 2010). Similarly, price spikes may result from demand inelasticity, exacerbated by the convexity of the supply curve, causing a disproportionate rise in equilibrium prices. In response, additional generators may enter the market at higher prices, eventually returning prices to their long-term averages. This mean-reversion tendency in electricity prices suggests a decline in volatility over longer maturities, a phenomenon known as the Samuelson effect (Samuleson, 1965). For non-storable commodities like electricity, market reactions to new information typically impact derivative prices more as they approach maturity.

The Brownian Motion (BM) model does not account for jumps in energy prices. Therefore, using BM to calculate volatility would reflect volatility changes due to energy policy and spikes or jumps caused by shifts in demand and supply-side shocks. To address these limitations, we incorporate parameters $\lambda, k, J(t)$ into the model to capture jump effects and estimate volatility adjusted for jumps. Initially, we adjust the drift term μ to $(\mu - \lambda k)$. Here, λ represents the annual number of jumps, and k denotes the mean size of price jumps, indicating how quickly the asset reverts to its long-term average. As the asset deviates from its average, the term λk pulls it back toward the mean. Jumps are defined as movements in returns that,

$$\mu_j - \sigma_j \geq \mu_j \geq \mu_j + \sigma_j \tag{2}$$

where μ_j, σ_j represent the mean and standard deviation of the time series data, respectively. Selecting one standard deviation aims to capture more jumps, offering a more comprehensive view of jump activity. A detailed derivation of k is provided in Matsuda (2004). This estimation approach, adapted from Tang (2018), involves computing $\hat{\lambda}$ and simulating a Merton jump-diffusion process. The calculation of λ *and* k depends on the data and is described in Eqs. (3) and (4):

$$\widehat{\lambda} = \text{the number of jumps per year} = \text{The total number of jumps} / \text{The total length in years} \tag{3}$$

$$k = \textit{the mean of the jump size} = \sum_{j=1}^{k} \frac{Jumpsize_i}{k} \tag{4}$$

where j = 1,2 … k , *jump size* generated from a normal distribution with mean and variance of the data points identified as jump. We then introduce an additional term to model the jumps and adjust for their effect on volatility, denoted as J_t. J_t = *jump size* * *probability(jump),* which functions to account for jumps occurring at any given time. Probability*(jump)* representing the probability of jumps occurring is represented in Eqs. (5) and (6).

$$probability(jump) = e^{-jump\ intensity * \Delta t} \tag{5}$$

$$Jump\ intensity = \frac{number\ of\ jumps\ per\ year}{total\ number\ of\ trading\ days} \tag{6}$$

Additionally, we employ a binomial random variable with parameters $n = 1$ and $p = e^{-jump\ intensity * \Delta t}$, where the jump intensity assumes arbitrary values within the range of 0–1. This binomial variable is utilized to ascertain the probability of upward and downward jumps at any given moment. By incorporating all these elements, we arrive at our final Mean-Reverting Jump Diffusion Model (MRJDM), as shown in Eq. (7).

$$S_{j+1} = S_j * (1 + (\mu - \lambda k)\ \Delta t + \sigma * \Delta W_j + J_t \tag{7}$$

The new model retains the underlying assumptions of BM (Hull and Basu, 2016), such as continuous trading without transaction costs, constant parameters μ,σ, and a non-paying dividend stock. Additionally, it assumes the price tends to revert to a long-term equilibrium level μ. Jumps occur randomly following a Poisson process with intensity λ, where each jump's size follows a normal distribution with mean and variance based on the jump data. These model assumptions align with those in Matsuda (2004), which utilized a Merton jump diffusion (MJD) model incorporating an exponential Levy process, assuming mean reversion and jumps following a compound Poisson process, with jump sizes distributed normally.

However, this model differs from MJD and BM in several ways: it assumes a Poisson process instead of a compound Poisson process, relaxes the log-normal distribution assumption of MJD to explore if the model still fits stock prices accurately, simplifies simulation equations compared to other mean-reverting jump-diffusion models, and employs the Nelder-Mead method for estimating drift and volatility terms, contrasting with Maximum Likelihood Estimation used in MJD.

The simulation results of the basic Brownian Motion defined in Eq. (1) are validated by comparing them with those of the model defined in Equation (7) using the average relative percentage error (ARPE) as an accuracy index, as shown in Eq. (8) (Areerak, 2014).

$$\text{ARPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|Y_i - \widehat{Y}_i|}{Y_i} \tag{8}$$

where N is the number of datasets, Y_i is the empirical price (market price), and $\widehat{Y}_i$ is the model price (simulated price).

The Nelder-Mead algorithm, also recognized as the simplex search algorithm, was initially introduced by Nelder and Mead in 1965. Renowned for its effectiveness in unconstrained optimization tasks without necessitating derivatives, this algorithm forms a robust foundation for parameter estimation. The estimation process commences with price simulation, employing Eq. (7).

The error is subsequently calculated by comparing simulated and actual spot prices. The mean square error is calculated by squaring these error values. The iterative minimization of this error is performed using the Nelder-Mead Algorithm. Price simulation and error calculation continue until the error converges to its minimum value or the maximum predefined number of iterations is reached. Given the arbitrary assumptions for various model terms, the estimation procedure is repeated 100 times. Following these iterations, the mean optimal values for both mean and volatility terms are extracted from pre- and post-policy periods to mitigate potential biases. Next, a hypothesis test is conducted on the volatility terms, where the null hypothesis H_0 posits that the volatilities before and after the policy change are not significantly different, and the alternative hypothesis H_1 asserts that they are significantly distinct. An F-test is employed to evaluate this hypothesis.

4.2. Proposed methodology for stochastic modelling

Fig. 2 illustrates the proposed methodology for stochastic modeling. Step 1: The initial dataset spanning from February 1, 2021, to February 1, 2023, is divided into pre-policy data (February 1, 2021, to February 1, 2022) and post-policy data (February 1, 2022, to February 1, 2023). Each dataset undergoes the same subsequent steps. Step 2: Jumps in the dataset are identified using Eq. (2), and $\widehat{\lambda}$ and jump intensity are estimated using Eqs. (3) and (6), respectively. Step 3: The model defined in Eqs. (1) and (7) is established, incorporating parameters dependent on random variables $k, \Delta W_j, J_t$. Other parameters are defined within the function and calculated using respective formulas. Step 4: The Nelder-Mead method optimises simulated prices by minimizing mean square error (MSE). Initially, with an initial guess (e.g., $\mu = 0.1$ *and* $\sigma = 0.1$), prices are simulated for N days (252 days). Parameters μ and σ are adjusted around the initial guess based on MSE performance: if MSE decreases, adjustments continue in that direction; otherwise, adjustments change direction. This process iterates for a maximum of N iterations (typically 100), and the average determines optimal μ and σ. Step 5: Once optimal μ and σ are identified, they are applied in the defined model to simulate index prices. Step 6: Simulated prices using BM and our model are evaluated based on the ARPE.

4.3. Sentiment predictions

In our analytical approach, we employ two distinct methods to examine sentiments. The initial method revolves around predicting the polarity of sentiments, distinguishing between positive and negative sentiments. Subsequently, our second method involves scoring the sentiments on a nuanced scale. Upon collecting Twitter data for sentiment prediction, our initial step entails leveraging the entire dataset to identify the optimal model for accurate sentiment prediction.

4.3.1. TextBlob

Initially, our analysis commences with examining sentiments using *TextBlob*, a Python library renowned for its comprehensive text mining, analysis, and processing modules designed for Python developers. This widely adopted method in research is exemplified through the provided codes in (Abiola et al., 2023). Drawing inspiration from diverse sources (Gujjar & Kumar, 2021; Abiola et al., 2023; Bonta et al., 2019), our methodology is enriched with insights from these scholarly contributions. *TextBlob* furnishes two key properties for a given input sentence: ***Polarity:*** This metric discerns the emotional tone conveyed in the statement, with values ranging from −1 to 1. Values closer to −1 signify a robust negative sentiment, while values nearing +1 indicate a pronounced positive sentiment. Values approaching zero suggest a neutral sentiment. ***Subjectivity:*** This property gauges personal sentiments, beliefs, and opinions, measured on a scale from 0 to +1. A value of

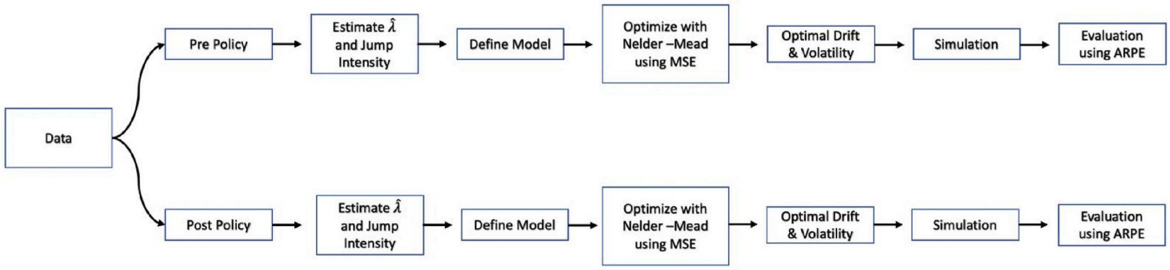

Fig. 2. Steps of stochastic modelling.

0 denotes high objectivity, while +1 indicates a high degree of subjectivity.

TextBlob selectively disregards unfamiliar terms and applies sentiment extremes and midpoints to words and expressions within its lexicon, culminating in a final score. Leveraging the *TextBlob* polarity function, we classify tweets as either positive or negative, with neutral tweets being excluded from our analytical purview due to their limited utility in our sentiment analysis.

4.3.1.1. Text data preprocessing using natural language processing (NLP). The methodology and codes applied in this process draw inspiration from the work of (Shekhar, 2021). NLP, a subfield of Artificial Intelligence, involves the intelligent and practical analysis, understanding, and extraction of meaning from human language by computers. The algorithm encompasses the following sequential steps:

Tokenization: As the initial step in NLP, tokenization involves three pivotal sub-steps: (i) Breaking down a complex sentence into individual words, (ii) Evaluating the significance of each word within the sentence, and (iii) Generating a structural description of the input sentence.

Stemming: Stemming normalizes words to their base form or root. For instance, words like "*Detected*", "*Detection*", "*Detecting*", and "*Detections*" share the root form "*Detect*". The Porter Stemmer is employed for this purpose. Stemming algorithms remove common suffixes and prefixes, though the precise root form may not always be obtained.

Lemmatization: This step groups together different inflected forms of words (lemmas) and maps them to their root form. Unlike stemming, lemmatization yields proper words and streamlines analysis by eliminating redundant data. For example, "*Gone*", "*Going*", and "*Went*" are all mapped to the common root "*Go*".

Data Cleaning: This involves the removal of stopwords, punctuation, and other unnecessary tokens to simplify processing. Stopwords, deemed trivial for analysis, are eliminated for more precise analysis. Punctuation is also removed from the token list.

4.3.1.2. Term-frequency times inverse document-frequency (TF-IDF). The TF-IDF method is employed to convert a set of words into numerical feature vectors. Commonly referred to as the 'Bag of Words' or 'Bag of n-grams' representation, this technique encompasses a specific approach to tokenization, counting, and normalization. The TF-IDF value for a term ' t' in a document ' d' is calculated using Eq. (9):

$$TFIDF\ (t,d) = TF\ (t,d) * \ IDF\ (t) \tag{9}$$

Here, the term frequency (*TF*) is the count of how often a term occurs in a document, and the Inverse Document Frequency (*IDF*) is calculated as in Eq. (10):

$$IDF(t) = log\frac{1+n_d}{1+df(t,d)} + 1 \tag{10}$$

Here, ' n_d' represents the total number of documents, and ' $df(t,d)$' is the number of documents containing the term ' t'. It is worth noting that in scikit-learn's *TfidfTransformer* and *TfidfVectorizer*, when using the '*smooth idf = False*' setting, the count ' 1' is added to the IDF instead of the denominator. The revised IDF formula is in Eq. (11):

$$IDF(t) = log\frac{1+n_d}{df(t,d)} + 1 \tag{11}$$

Following the TF-IDF calculation, the resulting vectors undergo normalization using the Euclidean norm in Eq. (12):

$$v_{norm} = \frac{v}{\sqrt{v_1^2 + v_2^2 + \ldots\ldots.. + v_n^2}} \tag{12}$$

This normalization process is implemented by the *TfidfTransformer* class. The TF-IDF technique is instrumental in preprocessing the data to fit a logistic regression model.

4.3.1.3. Bi-directional long short-term (BiLSTM) model. The methodology for this analysis is adapted from Cai et al. (2020), drawing on Long Short-Term Memory (LSTM) as an advanced model in comparison to Recurrent Neural Networks (RNN). LSTM addresses prevalent issues in RNNs, such as gradient explosion and vanishing gradients. It excels in handling sequences of varying lengths, mitigating the problem of rapid information loss in recurrent neurons (Hochreiter, 1998). LSTM comprises several components, including the input word at time ' t' denoted as x_t, the cell state c_t, temporary cell state $\widetilde{c}_t$, hidden layer state h_t, forgetting gate f_t, memory gate i_t, and output gate o_t. The operation of LSTM unfolds in three primary stages: the forgetting stage, the selective memory stage, and the output stage.

Forgetting Stage: Information in cells is selectively forgotten, with the retention of crucial information. The forgetting gate f_t governs this stage.

Selective Memory Stage: Information in the input cells is selectively "*remembered*", prioritizing important information while discarding unimportant data. The memory gate i_t controls this stage.

Output Stage: This stage determines the chosen information for the output and is regulated by the output gate o_t.

BiLSTM is composed of two parts: the forward LSTM and the backward LSTM. Unlike the forward LSTM, the backward LSTM processes the input sequence in reverse order and calculates the output similarly to the forward LSTM. By concatenating the outputs of the forward LSTM and the backward LSTM, the BiLSTM model considers both preceding and subsequent information, enhancing its ability to capture a comprehensive context.

4.3.2. Logistic regression

In addition to LSTM, logistic regression, as elucidated by (Majumder et al., 2021), is employed as a statistical method to assess the likelihood of the existence of a specific class, such as success/failure or win/lose scenarios. The logistic regression model is constructed with two predictors, denoted as x_1 and x_2, and one binary response variable labelled as J. The probability $p = P(J = 1)$ is represented as in Eq. (13):

$$I = \log\left(\frac{p}{1+p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \tag{13}$$

By applying algebraic concepts, the probability $P(J = 1)$ is derived as in Eq. (14):

$$P = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2)}} \quad (14)$$

Logistic regression utilizes the sigmoid function, as described above, to classify classes into negative and positive categories. The sigmoid function is instrumental in transforming the linear combination of input features into a probability score, facilitating the classification of observations into distinct classes.

4.3.2.1. Performance metrics. In evaluating the effectiveness of predictive models, a robust understanding of performance metrics is essential. This section elucidates the key metrics, including accuracy, recall, precision, and F1-Score, employed to assess model performance, alongside a comprehensive examination of the performance metrics specific to the fine-tuned BERT model, elucidating its accuracy under exact and off-by-one rating predictions. Our choice of these matrices is inspired by the work of Cai et al. (2020).

Accuracy: A commonly used criterion for assessing model performance. However, it can have limitations when dealing with unbalanced sample distributions. For instance, in a scenario where the negative sample ratio is exceptionally high (e.g., 99%), a model might achieve high accuracy by predicting all samples as negative. Accuracy is calculated in below Eq. (15):

$$\text{Accuracy} = n_{correct} / n_{total} \quad (15)$$

Recall: Also known as sensitivity or the true positive rate represented by the ratio of correctly identified true positive (TP) samples among all actual positive samples (True Positives, i.e., TP + False Negatives, i.e., FN). Higher recall values indicate the model's ability to identify more true positive samples. This is described in Eq. (16).

$$\text{Recall} = \frac{\text{TP}}{TP + FN} \quad (16)$$

Precision: Quantifies the proportion of TP predictions among all positive predictions, i.e., TP and False Positive (FP). It measures the model's ability to minimize false positives (see Eq. (17)).

$$\text{Recall} = \frac{\text{TP}}{TP + FP} \quad (17)$$

F1-Score: A metric that calculates the harmonic mean of precision and recall. It provides a balanced measure that considers both false positives and false negatives (see Eq. (18)).

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

The criteria for using evaluation metrics such as accuracy, precision, F1-score, and recall stem from their widespread application in classification tasks. These metrics are essential to verify if the model fits well and to ensure its ability to predict unseen data accurately. Without precision and recall, identifying biases in the model's predictions would be challenging, if not impossible.

4.3.2.2. Bidirectional encoder representations from transformers (BERT). BERT employs a deep architecture with six layers of Transformer models stacked on both the encoder and decoder. This complexity and the resource-intensive nature of its training contribute to extended training times and substantial computational costs (Cai et al., 2020).

However, Google has made pre-trained BERT models accessible to the public. Specifically, the BERT-base-multilingual-uncased model, pre-trained on the top 102 languages using a masked language modeling (MLM) objective, is available (Devlin et al., 2018). The detailed architecture of the BERT model is described by Vaswani et al. (2017).

BERT pre-trains language representations on a large text corpus (like Wikipedia) for general-purpose language understanding, which can then be used for downstream NLP tasks (such as question answering). Using BERT involves two stages: pre-training and fine-tuning. Pre-training is expensive (requiring four days on 4 to 16 Cloud TPUs) but is a one-time procedure for each language. BERT variants are widely available in TensorFlow and GitHub, so most NLP researchers will not need to pre-train their own models from scratch.

Fine-tuning, however, is inexpensive. It involves adapting the pre-trained model to specific data and tasks. BERT's adaptability to various NLP tasks is significant (Devlin et al., 2018). In our case, the model is already pre-trained and fine-tuned, so we can proceed to use it directly for sentiment-scoring tasks.

The model used in this study is BERT-base-multilingual-uncased-sentiment, fine-tuned for sentiment analysis on product reviews in multiple languages (English, Dutch, German, French, Spanish, and Italian). It predicts the sentiment of reviews by assigning star ratings ranging from 1 to 5. The performance metrics for this fine-tuned BERT model are as follows:

Accuracy (Exact): The percentage of reviews for which the model's star rating prediction exactly matches the human reviewer's rating is 67%.

Accuracy (Off-by-1): This metric represents the percentage of reviews where the model's star rating prediction differs by, at most, 1 star from the rating given by the human reviewer, achieving an accuracy rate of 95%.

4.4. Proposed methodology for sentiment scoring and sentiment prediction

Fig. 3 illustrates the proposed methodology for sentiment scoring and sentiment prediction.

For sentiment scoring, the BERT-based multilingual-uncased model, which is pre-trained with built-in functions, scores sentiments on a scale from 1 to 5 based on the positivity of the text. Initially, the data is split into pre-policy and post-policy datasets. Each dataset is then fed into the pre-trained BERT tokenizer, which converts words into tokens, a list of integers representing each unique word. For example, "I love natural language processing!" is tokenized using the pre-trained BERT as ([101, 151, 11157, 11753, 12823, 32954, 106, 102]). Similarly, all texts are converted into tokens. These tokens are then used as input for the pre-trained BERT sentiment scoring model, which assigns a sentiment score from 1 to 5. For sentiment prediction, all data is initially pre-processed using NLTK. The text is first converted into tokens, where tokens are individual words, unlike in the pre-trained BERT. These tokens are then stemmed, lemmatized, and stop words are removed, with the remaining words of the tweet combined to form the preprocessed text. This preprocessed text is then analyzed using TextBlob to classify the text as positive, negative, or neutral. Neutral tweets are removed from the dataset, leaving only positive and negative tweets. The number of positive and negative tweets is then counted to check for class imbalance. If there is a significant class imbalance, the class with more tweets is resampled to match the number of tweets in the less frequent class, ensuring the model fits well and is not biased towards the majority class. These tweets are then split into train and test datasets, with 80% used for training and the remaining 20% for testing. The training data is used to train the models, and the test data is used to evaluate the trained models.

5. Findings and discussions

5.1. Stochastic modelling using MRJDM

Before the American Energy Independence and Security Act, optimal values for the variables were determined as follows: λ = 50, μ = 0.00399, σ = 0.02849, and Jump intensity = 0.19920 (the Poisson parameter). Subsequently, Eq. (19) was identified for simulating future prices.

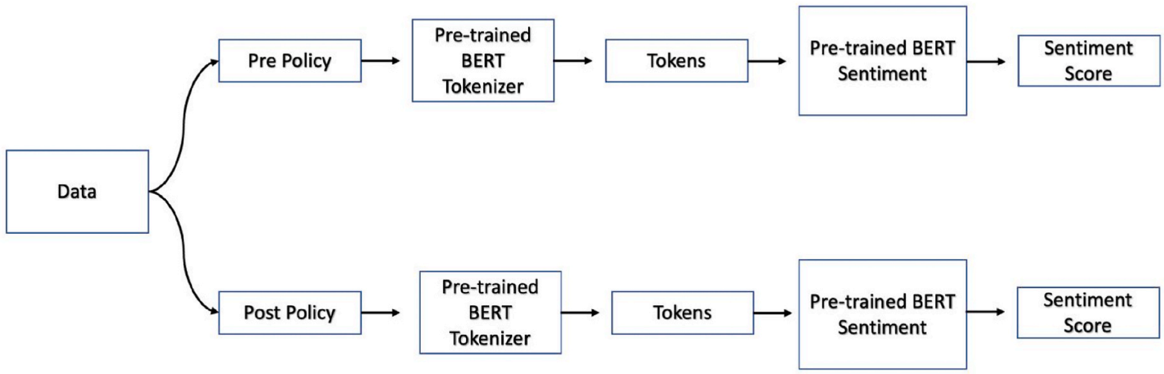

Fig. 3. Proposed methodology for sentiment scoring and sentiment prediction.

$$S_{j+1} = S_j * \left(1 + (0.00399 - 50\boldsymbol{k})\ \frac{1}{252} + 0.02849 * \Delta W_j + J_t\right) \tag{19}$$

After the Act, the optimal values changed to $\lambda = 76$, $\mu = 0.00222$, $\sigma = 0.02538$, and Jump intensity $= 0.30769$. The corresponding simulation Eq. (20) was derived, with other variables on the right-hand side assigned arbitrarily.

$$S_{j+1} = S_j * \left(1 + (0.00222 - 76\boldsymbol{k})\ \frac{1}{252} + 0.02538 * \Delta W_j + J_t\right) \tag{20}$$

Eq. (19) was used to simulate the index price from February 1, 2021, to February 1, 2022, covering approximately 252 days. Similarly, Eq. (20) was used to simulate the index price from February 1, 2022, to February 1, 2023, also for approximately 252 days. The resulting simulated prices from each period are then evaluated against the actual spot prices. Concurrently, for the same periods, the BM simulated prices before the policy is represented by Eq. (21), and after the policy, the BM model for simulating prices is represented by Eq. (22).

$$S_{j+1} = S_j * \left(1 + (0.00400)\ \frac{1}{252} + 0.02863 * \Delta W_j\right) \tag{21}$$

$$S_{j+1} = S_j * \left(1 + (0.00224)\ \frac{1}{252} + 0.02546 * \Delta W_j\right) \tag{22}$$

Here, the μ obtained represents the expected rate of return per unit of time (one day in this context) and σ signifies the volatility per unit of time. A comparison of the models Before and after the policy using ARPE is presented in Fig. 4 and Table 2.

This demonstrates that the MRJDM is better than the BM at simulating index prices both before and after the policy. In Fig. 4, the blue line represents actual prices, and the orange line represents simulated prices. The MRJDM graphs before and after the policy show that the simulated prices are consistently positive. Numerous iterations of the MRJDM consistently yielded positive price movements. Despite differences in values, statistical analysis, reflected in an F-statistic of 1.26 and an F-critical value of 1 at a 5% level of significance, did not support the rejection of the null hypothesis, indicating no significant difference in volatilities before and after the Act.

Table 2
Model comparison.

	MRJDM	BM
Before Policy	15.509	27.255
After Policy	20.464	27.267

5.2. Experiments with sentiment predictions

Two additional machine learning models, Random Forest and RoBERTa-Base, are employed alongside the earlier logistic regression model to provide a broader perspective on tweet prediction.

5.2.1. Random forest

Random Forest, an ensemble of decision trees, serves as a powerful algorithm that amalgamates the outputs of multiple trees through the application of bagging. This approach fosters the creation of a diverse set of trees by training each tree on a random subset of the data. The ultimate prediction is made by aggregating the majority vote from all the constituent trees. This ensemble technique effectively mitigates

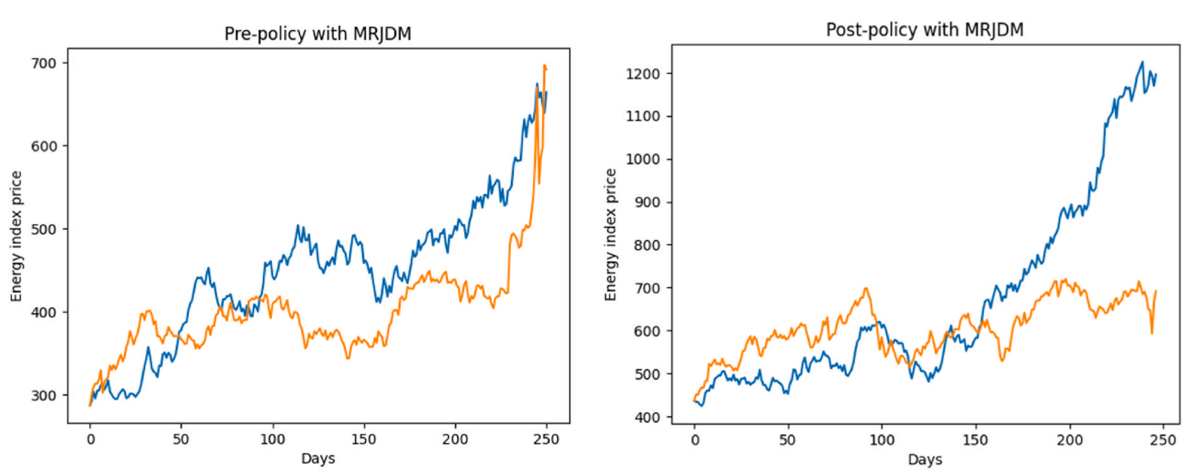

Fig. 4. The graphs for MRJDM.

overfitting concerns, enhances model accuracy and stability, and bolsters the model's generalization capability to unseen data. The random forest algorithm, conveniently available in the sci-kit-learn library, offers a feature importance attribute that facilitates the assessment of feature significance, serving as a valuable tool. We use this model to check whether a simple model performs better than a complex model with a smaller dataset.

5.2.2. RoBERTa-base

RoBERTa-Base was also used, a model trained on approximately 58 million tweets and fine-tuned for sentiment analysis with the TweetEval benchmark. This model, suitable for English, can directly classify the test data into positive or negative classes. By incorporating this model, experimental settings were adjusted to observe their impact on the accuracy of tweet predictions.

5.2.3. With NLTK text preprocessing and under-sampling

With text data preprocessing and under-sampling, two models, Logistic Regression and RoBERTa, emerged superior to all other models (refer to Table 3).

5.2.4. Without NLTK text preprocessing and under-sampling

Here, Logistic Regression and Random Forest models were superior to others, closely followed by RoBERTa (refer to Table 4). Interestingly, without NLTK preprocessing, the accuracy of all models increased, suggesting that text preprocessing, typically used to clean data, may inadvertently remove useful information, potentially enhancing training speed for deep learning models. However, losing valuable information remains a concern with small datasets like that in our study.

5.2.5. With NLTK text preprocessing and without under-sampling

RoBERTa has outperformed all other models (see Table 5). Despite Logistic Regression having higher precision than RoBERTa, it falls short on other metrics. The higher precision and lower accuracy of Logistic Regression and Random Forest indicate a bias towards the majority class, as precision and recall are metrics used to detect class bias. RoBERTa's exceptional performance, despite class imbalance, can be attributed to its training on a large dataset of tweets. Deep learning models like RoBERTa are computationally intensive but perform better when trained on large datasets.

5.2.6. Without NLTK text preprocessing and without under-sampling

A similar pattern emerges in experiments without under-sampling, where logistic regression and Random Forest perform inadequately, while Roberta proves to be the top-performing model (refer to Table 6). The key findings from these experiments are as follows: A well-trained deep learning model like Roberta trained on a large dataset delivers robust performance regardless of dataset size, quality, preprocessing, or class imbalance. In contrast, using a small dataset without pre-training deep learning for text classification yields unsatisfactory results. NLTK preprocessing is highly effective in large datasets, enhancing performance in deep learning models, but its suitability diminishes for smaller datasets. Under-sampling can prevent models from fitting inaccurately, as evidenced by the superior results observed with under-sampling compared to those without. Combining preprocessing with under-sampling in small datasets enables simpler models to learn effectively and make accurate predictions.

Table 3
Models accuracy.

	Accuracy	precision	recall	f1-score
Logistic Regression	**0.65**	**0.65**	**0.65**	**0.64**
Random Forest	0.57	0.58	0.57	0.57
LSTM	0.5	0.25	0.5	0.33
Bi-LSTM	0.5	0.25	0.5	0.33
Roberta	**0.65**	**0.65**	**0.65**	**0.65**

Table 4
Models accuracy.

	Accuracy	precision	recall	f1-score
Logistic Regression	**0.7**	**0.7**	**0.7**	**0.7**
Random Forest	**0.7**	**0.7**	**0.7**	**0.7**
LSTM	0.51	0.25	0.5	0.34
Bi-LSTM	0.51	0.25	0.5	0.34
Roberta	**0.68**	**0.7**	**0.68**	**0.67**

Table 5
Models accuracy.

	Accuracy	precision	recall	f1-score
Logistic Regression	0.65	**0.72**	0.54	0.48
Random Forest	0.67	0.7	0.58	0.55
LSTM	0.38	0.19	0.5	0.27
Bi-LSTM	0.38	0.19	0.5	0.27
Roberta	**0.67**	**0.65**	**0.65**	**0.65**

Table 6
Models accuracy.

	Accuracy	precision	recall	f1-score
Logistic Regression	0.71	**0.85**	**0.51**	0.44
Random Forest	0.73	0.72	0.55	0.53
LSTM	0.3	0.15	0.5	0.23
Bi-LSTM	0.3	0.15	0.5	0.23
Roberta	**0.68**	**0.63**	**0.64**	**0.63**

5.2.7. Sentiment score prediction

The average sentiment score decreased slightly from 2.852 before the EISA to 2.617 afterwards.

5.2.8. Sentiment prediction

Performance metrics for logistic regression and bidirectional LSTM models with under-sampling and NLTK data preprocessing are summarized in Table 7. Logistic regression achieved an accuracy of 0.65, precision of 0.65, recall of 0.65, and F1-score of 0.64. The bidirectional LSTM model demonstrated an accuracy of 0.50, precision of 0.25, recall of 0.50, and F1-score of 0.33.

Detailed confusion matrices for sentiment prediction using logistic regression (Table 8) and bidirectional LSTM (Table 9) are provided, demonstrating correct and incorrect predictions for each model.

In the context of sentiment prediction, where 0 signifies negative predictions, and 1 denotes positive predictions, the logistic regression algorithm (see Table 8) achieved 53 accurate predictions (23 + 30) and 29 incorrect predictions (11 + 18). The bidirectional LSTM algorithm demonstrated 41 accurate and 41 incorrect predictions (see Table 9). This detailed breakdown provides insights into the model's performance, distinguishing between negative and positive sentiments.

5.3. Discussions

This investigation into energy market volatility, employing a mean-reverting-jump-diffusion model, reveals that volatility before and after the enactment of the EISA showed no significant difference. This finding suggests sustained stability in the S&P Energy Index, a reliable proxy for

Table 7
Metrics of the models.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	**0.65**	**0.65**	**0.65**	**0.64**
Bidirectional LSTM	0.50	0.25	0.50	0.33

Table 8
Confusion Matrix for Sentiment Prediction using Logistic Regression.

	Predicted (0)	Predicted (1)
Actual (0)	23	18
Actual (1)	11	30

Table 9
Confusion Matrix for Sentiment Prediction using Bidirectional LSTM.

	Predicted (0)	Predicted (1)
Actual (0)	41	0
Actual (1)	41	0

US energy markets. Notably, returns in the period after the implementation of the EISA exhibit an increase, which is evident from the means presented in the data section. This result implies that investors and traders can confidently engage in market positions, benefitting from relatively constant risk while enjoying enhanced returns.

The sentiment score before and after the implementation of the EISA maintains a positive outlook, albeit with a slight reduction. This diminution could be associated with the broader volatility observed in global energy markets (Liu et al., 2023). Despite this minor decrease, the persistently positive sentiment, coupled with the influence of the American Energy Independence and Security Act, is anticipated to bolster investor confidence in the energy markets. A similar argument was made by Ur Rehman et al. (2023). Consequently, investors will likely find opportunities for long-term and short-term positions within the energy market.

Hence, it is evident that a positive sentiment endures when there is no significant deviation in volatility across different periods. We emphasize that this correlation does not imply causation. Despite the EISA of 2022 playing a central role in all applied methodologies, the study finds that volatility remains largely unaffected by the Act, while returns exhibit improvement. This positive shift in returns could be attributed to favorable investment sentiments and the sustained stability in volatilities both before and after the enactment of the Act. Despite a slight reduction in positive sentiment, the enduring stability in volatility and optimistic sentiments indicates the continued feasibility of investing in energy markets.

Previous research by (Ge et al., 2018) and (Hou et al., 2021) has demonstrated that LSTM outperforms basic machine learning models to a marginal extent. However, this study diverges from that trend, encountering a scenario where the Bidirectional LSTM (BiLSTM) model overfits the data, particularly in identifying the positive class, as evidenced by the zero column in the confusion matrix. In contrast, the Logistic Regression model proves notably superior to BiLSTM. Sometimes, a simpler model, such as Logistic Regression, can prove more effective than a complex counterpart like BiLSTM, especially when the latter fails to deliver optimal performance. Consequently, the outlook for a significantly more intricate model, such as BERT-BiLSTM, may not be promising in this context.

6. Conclusions

The present study examines the impact of the EISA of 2022 on market volatility. It deploys an innovative Mean-Reverting Jump Diffusion Model (MRJDM) to examine the market volatility. The estimates display no statistically significant difference in volatility before and after implementing the AEISA of 2022. Similarly, various BERT-base-multilingual-uncased models with logistic regression and Bidirectional LSTM are utilized to assess sentiment predictions. The evaluations show the superiority of logistic regression over Bidirectional LSTM for the small dataset. However, the performance of RoBERTa remains unparalleled despite data imbalances and the absence of data preprocessing. This result underscores the potential of neural networks to outperform other methods when provided with substantial amounts of text data for training, regardless of data quality.

The overall study findings indicate that the S&P energy index is relatively stable despite major policy reforms, and investors may benefit by holding energy stocks in their portfolios during market turmoil. It also indicates the policy's success in strengthening the energy sector without affecting economic stability. The present study uniquely explored the interplay between volatility and investor sentiment, contributing valuable insights for informed financial decision-making across long- and short-term horizons. These aspects represent promising research directions that could contribute significantly to the existing body of knowledge in the field. It is important to note that market anomalies or catastrophic events can distort model efficiency. This limitation of the present study could serve as a direction for future research to improve the models used in this study. Future research could explore the applications across energy sub-sectors and cross-national comparisons. An interdisciplinary analysis could also examine broader aspects of EISA of 2022, drawing on economics, environmental science, political science, sociology, and technology to consider supply chain dynamics, geopolitical influences, and climate change.

CRediT authorship contribution statement

Hiridik Rajendran: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Parthajit Kayal:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Formal analysis, Conceptualization. **Moinak Maiti:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

There is no conflict of interest.

Data availability

Data will be made available on request.

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