The impact of news on investment habits

Yohann Akale(yohann@ualberta,ca), Gurkirat singh(gurkira4@ualberta.ca)

December 2024

Introduction

Financial markets are highly dynamic systems, influenced by a multitude of factors ranging from macroeconomic indicators to individual investor behavior. Among these, **news** stands out as a critical driver of market activity. News events, whether they are related to corporate announcements, geopolitical developments, or broader economic policies—can trigger significant changes in stock prices, volatility, and investor sentiment. These effects are often abrupt, non-linear, and difficult to predict, varying greatly in intensity based on the timing, nature, and perceived importance of the news.

This project seeks to explore these phenomena through a robust mathematical framework, leveraging advanced stochastic modeling techniques. By integrating **jump-diffusion processes**, the **Heston stochastic volatility model**, a **stochastic jump intensity process**, and a **Markov chain for market sentiment**, which is uncommon in financial modeling, this framework provides a comprehensive tool to understand and simulate the impact of news on financial markets by analyzing three different sectors namely; **Technology**, **Energy** and **Health**.

Problem Setup

We both have personal portfolios that we actively manage, and our experiences with these investments served as the motivation for taking up this project. During the COVID-19 pandemic, in particular, we noticed how news announcements caused significant fluctuations in the value of our portfolios. Whether it was related to vaccine approvals, lockdown measures, or fiscal policies, the market reacted sharply, often resulting in dramatic changes in stock prices and volatility. Even outside of the pandemic, we observed similar patterns during regular news announcements, such as earnings reports or regulatory updates. This led us to ask an important question: **Is there a correlation between news events and stock price movements?** If so, could we use this information to make more informed investment decisions and improve our portfolio performance?

In addition to enhancing our investment strategies, we also wanted to apply this project to **risk management** as part of our future explorations with the model. Market shocks caused by unexpected news can lead to significant losses for investors, especially when portfolios are not adequately hedged. Understanding how news impacts stock prices and volatility could help investors anticipate and mitigate such risks. By incorporating news-driven dynamics into a financial model, we hoped to provide a tool that not only aids in identifying potential opportunities but also enhances the ability to manage risks effectively. For example, if certain types of news are associated with increased volatility, investors can adjust their portfolios or employ hedging strategies to limit downside exposure during such periods.

Traditional financial models, such as the Black-Scholes model, assume stock prices follow a smooth, continuous trajectory driven by Brownian motion. Although this approach simplifies calculations, it overlooks sudden jumps caused by unexpected news. For instance, regulatory announcements or technological breakthroughs can lead to sharp, discrete changes in stock prices that these models fail to capture. This limitation became particularly apparent as we tried to analyze the erratic movements in our portfolios during major news events.

To address this gap, jump-diffusion models combine gradual price changes with sudden jumps, offering a more realistic representation of market behavior. However, these models rarely incorporate the role of market sentiment, which is often shaped by news and can significantly influence price movements; and this was the novel aspect of this project. By including news-driven sentiment dynamics in financial models, we can better understand and simulate the interaction between investor psychology, market sentiment, and stock price fluctuations, providing a more complete view of real-world market behavior.

The problem we aimed to solve therefore was to develop a comprehensive mathematical framework that accounts for the effects of news on stock prices, volatility, and market sentiment. Specifically, we sought to answer the following questions:

1. **How do sudden news events impact stock price dynamics and volatility?**

2. **Can we model the influence of news on market sentiment and its cascading effect on price movements?**

3. **How can these insights be used to improve investment decisions and apply effective risk management strategies?**

By addressing these questions, this project not only provides a theoretical understanding of how news influences financial markets but also offers practical applications for investors like ourselves. Our ultimate goal is to develop a tool that captures these dynamics, helping investors predict and navigate market fluctuations more effectively while mitigating risks associated with unexpected shocks.

Mathematical Framework

The mathematical framework used in this project consists of four interconnected components: **stock price dynamics**, **variance dynamics**, **stochastic jump intensity**, and **market sentiment dynamics**. Each component is carefully designed to reflect the complex interplay between market forces, investor behavior, and news events.

Our model evolved through a series of refinements. Initially, we experimented with simpler formulations, but these approaches proved inadequate in addressing the intricacies of real-world market behavior. The current model integrates jump-diffusion processes, the Heston stochastic volatility model, stochastic intensity processes, and a Markov chain for sentiment dynamics.

Initial Stock Price Dynamics and Transition to Jump-Diffusion Process

Our initial attempt modeled stock price dynamics as:

$$dS_t = \mu S_t \, dt + \sigma_t S_t \, dW_t + S_t \sum_{i=1}^{N_t} (J_i - 1).$$

Here:

- $\mu S_t \, dt$: Represents deterministic drift due to the growth rate μ.
- $\sigma_t S_t \, dW_t$: Captures continuous random fluctuations, here σ_t is the volatility of the stock. This section of the equation was the diffusion coefficient
- $S_t \sum_{i=1}^{N_t} (J_i - 1)$: Models price jumps driven by a Poisson process N_t, with jump magnitudes $J_i - 1$. By summing over all jumps, we get the total net effect of all news events up to that point in time.

However, this equation had significant shortcomings:

- **Unidirectional Jumps:** The shocks $J_i - 1$ were positive by construction, limiting the ability to model negative price movements, such as those caused by adverse news.
- **Uncompensated Process:** The absence of compensation caused a systematic upward drift in the jump component, making the process unrealistic over time. Also we needed this term to be a diffusion and martingale in order for the equation to be a stochastic differential equation

Recognizing these issues, we adopted a jump-diffusion process with a compensated Poisson random measure, ensuring that jumps could be both positive and negative and the process remained a martingale. The updated stock price dynamics are:

$$dS_t = r S_t \, dt + \sqrt{V_t} S_t \, dB_t + S_t \int_{\mathbb{R}} (z - 1) \tilde{N}(dt, dz).$$

Here:

- $r S_t \, dt$: Represents deterministic drift due to the risk-free rate r.
- $\sqrt{V_t} S_t \, dB_t$: Captures continuous fluctuations, where V_t is variance and B_t is Brownian motion.

- $S_t \int_{\mathbb{R}} (z-1)\tilde{N}(dt, dz)$: Models discrete jumps caused by news, with $\tilde{N}(dt, dz)$ as a compensated Poisson random measure. The compensation ensures the jump process remains a martingale, avoiding systematic drift.

Why Poisson Measure? Unlike a basic Poisson process, a Poisson measure allows for modeling jump magnitudes $z-1$ with a specific distribution $\nu(dz)$. This flexibility is critical for capturing the varied impacts of news, from minor fluctuations to major shocks.

Variance Dynamics: Transition to Heston Model

Initially, we employed an Ornstein-Uhlenbeck (OU) process to model variance V_t:

$$dV_t = \kappa(\theta - V_t)\, dt + \eta\, dW_t.$$

While the OU process is mathematically simple and mean-reverting, it suffered from a critical drawback: negative variance values, which are physically and financially unrealistic. Variance, as a squared term, cannot be negative.

To address this, we transitioned to the Heston stochastic volatility model that we found on the paper written by **Sergei Mikhailov, Ulrich Nögel** called "**Heston's Stochastic Volatility Model Implementation, Calibration and Some Extensions**", widely used in financial modeling(Paper linked in the appendix). The updated variance dynamics are:

$$dV_t = \kappa(\theta - V_t)\, dt + \eta\sqrt{V_t}\, dW_t + \int_{\mathbb{R}} \xi(z)\tilde{N}(dt, dz).$$

Here:

- $\kappa(\theta - V_t)\, dt$: Ensures mean reversion to the long-term average θ at rate κ.
- $\eta\sqrt{V_t}\, dB_t$: Adds randomness to variance, proportional to $\sqrt{V_t}$.
- $\int_{\mathbb{R}} \xi(z)\tilde{N}(dt, dz)$: Captures jumps in variance due to news events, with $\xi(z)$ as the jump size.

Stochastic Intensity Process: Transition to CIR Model

Initially, we modeled the occurrence of news-driven jumps using a Poisson jump process. In this approach, the jump sizes for stock price and volatility were assumed to follow a normal distribution:

$$J_i \sim \mathcal{N}(\mu_J, \sigma_J^2), \quad \xi_i \sim \mathcal{N}(\mu_\xi, \sigma_\xi^2),$$

where J_i represents the jump size for stock price and ξ_i represents the jump size for volatility. While this approach provided a straightforward way to model discrete events, it had a critical limitation: the rate of jumps was fixed and could not vary over time. This limitation was particularly problematic when modeling real-world markets, where the frequency of news events can fluctuate significantly. For instance, during periods of market uncertainty or crises, news tends to cluster, leading to higher jump intensities, whereas in calmer periods, jump intensities decrease.

To address this shortcoming, we transitioned to a Cox-Ingersoll-Ross (CIR) process for modeling the stochastic jump intensity λ_t. The CIR process dynamically adjusts the rate of jumps, allowing the model to simulate periods of high or low news intensity. Throughout extensive research we used the model from "**On the Jump Dynamics and Jump Risk Premiums**" published by **Gang Li** that helped us find the best equation for the CIR model. The updated intensity dynamics are given by:

$$d\lambda_t = \alpha(\beta - \lambda_t)\, dt + \delta\sqrt{\lambda_t}\, dZ_t,$$

where:

- λ_t: Represents the stochastic rate of news events.
- $\alpha(\beta - \lambda_t)$: The mean-reversion term ensures that λ_t reverts to its long-term mean β at a speed determined by α.
- $\delta\sqrt{\lambda_t}\, dZ_t$: Adds randomness to λ_t, where dZ_t is a Brownian motion.

The CIR process offers several advantages over the initial Poisson jump process. First, it allows for dynamic variation in jump rates, which aligns better with real-world behavior. For example, during an earnings season or a geopolitical crisis, the model can simulate increased jump intensity by increasing λ_t. Second, the mean-reversion property of the CIR process ensures that λ_t does not grow indefinitely or drop to zero, maintaining stability over time. Finally, the inclusion of randomness through $\delta\sqrt{\lambda_t}\, dZ_t$ captures unexpected spikes in news intensity, further enhancing the model's realism.

This transition to the CIR process significantly improved the model's ability to capture real-world dynamics, making it more adaptable to varying market conditions. For example, in our simulations, we observed that the CIR process effectively modeled periods of high volatility during financial crises and lower volatility during stable economic conditions.

Final stock price dynamics equation

Moreover, after all these rectifications we were also advised to replace the risk free rate r, so we decided to changed it to a growth factor μ. As a final equation we obtained this equation:

$$\boldsymbol{dS_t = \mu S_t\, dt + \sqrt{V_t} S_t\, dB_t + S_t \int_{\mathbb{R}} (z-1) \tilde{N}(dt, dz).}$$

- μ is a deterministic drift composed of a coefficient and the magnitude of the news.

Market Sentiment Dynamics

Market sentiment is modeled as a **Markov process** with three discrete states: bullish, neutral, and bearish. Transition probabilities are represented by:

$$P = \begin{bmatrix} p_{BB} & p_{BN} & p_{BE} \\ p_{NB} & p_{NN} & p_{NE} \\ p_{EB} & p_{EN} & p_{EE} \end{bmatrix}.$$

Here, p_{ij} represents the probability of transition from state i to state j. The novel aspect of our model is its integration of market sentiment using a Markov chain. Sentiment states (bullish, bearish, neutral) evolve based on transition probabilities influenced by news. For example, positive news increases the likelihood of transitioning to a bullish state. This behavioral component provides deeper insights into investor psychology and market trends. In this matrix, p_{BN} is the probability that the market sentiment will go from bullish to neutral and where p_{NE} is neutral to bearish and so on.

The key benefit of using a Markov chain is that it allows for discrete changes in sentiment, reflecting the noncontinuous nature of market psychology. Sentiment transitions are not smooth or predictable but depend on various factors such as news events, investor behavior, and macroeconomic conditions. The transition probabilities capture these shifts, making the model more realistic by accounting for sudden changes in market trends, such as bullish rallies or bearish corrections.

Methodology/Code implementation

Our project required the development of a Python-based simulation to model stock price dynamics, volatility, and market sentiment influenced by news events.Below, we outline the methodology, including assumptions, parameters, and an explanation of the implementation.

Assumptions in the Implementation

- **Trading Days**: We assumed 252 trading days in a year to match standard financial conventions.

- **Risk-Free Rate**: The risk-free rate used was $r = 4.3\%$, reflecting 2024 data.

- **Sector simplification**: For simplicity, the model focuses on three sectors: Technology, Health, and Energy.

- **Initial Market Sentiment**: The market starts in a **neutral sentiment state**, reflecting average conditions.

- **Fixed Jump Parameters**: To simplify computations, jump size distributions were fixed rather than dynamically varying.

- **Markov Chain Probabilities**: Market sentiment transitions (bullish, neutral, bearish) were triggered by news events, and probabilities were predefined and updated based on the news.

- **Impact Strength**: The impact of the news was normalized between 0 and 1, allowing us to scale its influence on market sentiment and stock prices.

- **Historical News Events**: News events and their attributes were derived from real-world data corresponding to the time period studied which are linked in the appendix

We analyzed the market sentiment for the studied sectors (Technology, Health, Energy) and manually determined whether the market was likely to remain bullish, bearish, or neutral during specific periods. These probabilities were input into the Markov chain, ensuring sector-specific accuracy. Additionally, fixed jump parameters were used to simplify the implementation, although these can be adjusted to reflect subtle real-world changes.
This methodology demonstrates the versatility of our model and its potential applications in simulating stock price dynamics and volatility under varying market conditions.

Model Parameters

The key parameters of the model, such as θ, α, β, and others, were inferred from research into the specific sectors being modeled. This ensured sector-specific realism in the simulations. Below is a summary of key parameters used for the Energy Sector stock that is **Exxon mobil(XOM)** but were adjusted accordingly for the Technology and Health Sectors (additional relevant parameters can be found in the appendix):

- **Variance Dynamics** (Heston Model):
- $\boldsymbol{\kappa = 2}$: Speed of mean reversion for variance.
- $\boldsymbol{\theta = 0.04}$: Long-term mean of variance.
- $\boldsymbol{\eta = 0.4}$: Volatility of variance.
- $\boldsymbol{v_0 = 0.1846}$: Initial variance.

- **Jump Intensity** (CIR Process):
- $\boldsymbol{\alpha = 0.1}$: Speed of mean reversion for jump intensity.
- $\boldsymbol{\beta = 1.88}$: Long-term mean jump intensity.
- $\boldsymbol{\delta = 0.15}$: Volatility of jump intensity.

- **Jump Parameters**:
- Stock Price Jumps: mean $=$ **0.03**,
volatility $=$ **0.06**.
- Volatility Jumps: mean $=$ **0.04**,
volatility $=$ **0.15**.

Implementation Details

Drift is adjusted based on sentiment and magnitude of the news:
- Bullish: $0.05 +$ impact strength.
- Neutral: 0.

- Bearish: 0.05 − impact strength.

The jump intensity λ itself follows a Cox-Ingersoll-Ross (CIR) process, which enables it to vary over time, capturing periods of high and low market activity. Market sentiment transitions are guided by a Markov chain, with probabilities influenced by the nature of news events. For instance, positive news increases the likelihood of transitioning to a bullish state, while negative news raises the probability of entering a bearish state. News events were randomly sampled from a curated dictionary of historical events, with relevance to the sector determining their influence. The impact strength of these events was calculated and integrated into the drift dynamics, ensuring that the drift component of the SDE reflects the effect of external information. This comprehensive approach allowed us to capture the interplay between market sentiment, volatility, and random shocks in the evolution of the stock price. **Refer to Figure 1,2,3 in appendix A to see the implentation of these equations as code**.

Example Simulation: Exxon Mobil

The code implementation for Exxon Mobil (2007–2024) demonstrates the model's functionality. Key highlights include:

1. **Initialization**:

- Define parameters: S_0, v_0, λ_0, and sentiment state.
- Load sector-specific news events such as "Record Profits Amid Rising Oil Prices" and "Gulf of Mexico Spill Scrutiny" from a dictionary.

2. **Iteration** (Per Trading Day):

- Sample news events every 25 steps to update sentiment probabilities.
- Update sentiment state using the Markov chain.e.g Positive energy sector news increased the probability of bullish sentiment, while negative news, like environmental scrutiny, raised bearish probabilities.
- Simulate jump intensity with the CIR process.
- Update variance using the Heston process.
- Compute stock price using jump-diffusion dynamics.

3. **Output**:

- Plot stock price, variance, jump intensity, and sentiment state over time.
- Print news events and their sector-specific impacts for analysis.

4. **Market sentiment**:

- For the market sentiment these are the two matrix we used for the implementation of positive and negative news(with the new markov chain after a positive news on the left):

$$P = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.8 & 0.15 & 0.05 \\ 0.8 & 0 & 0.2 \end{bmatrix} P = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.15 & 0.8 \\ 0.05 & 0.05 & 0.9 \end{bmatrix}.$$

Results

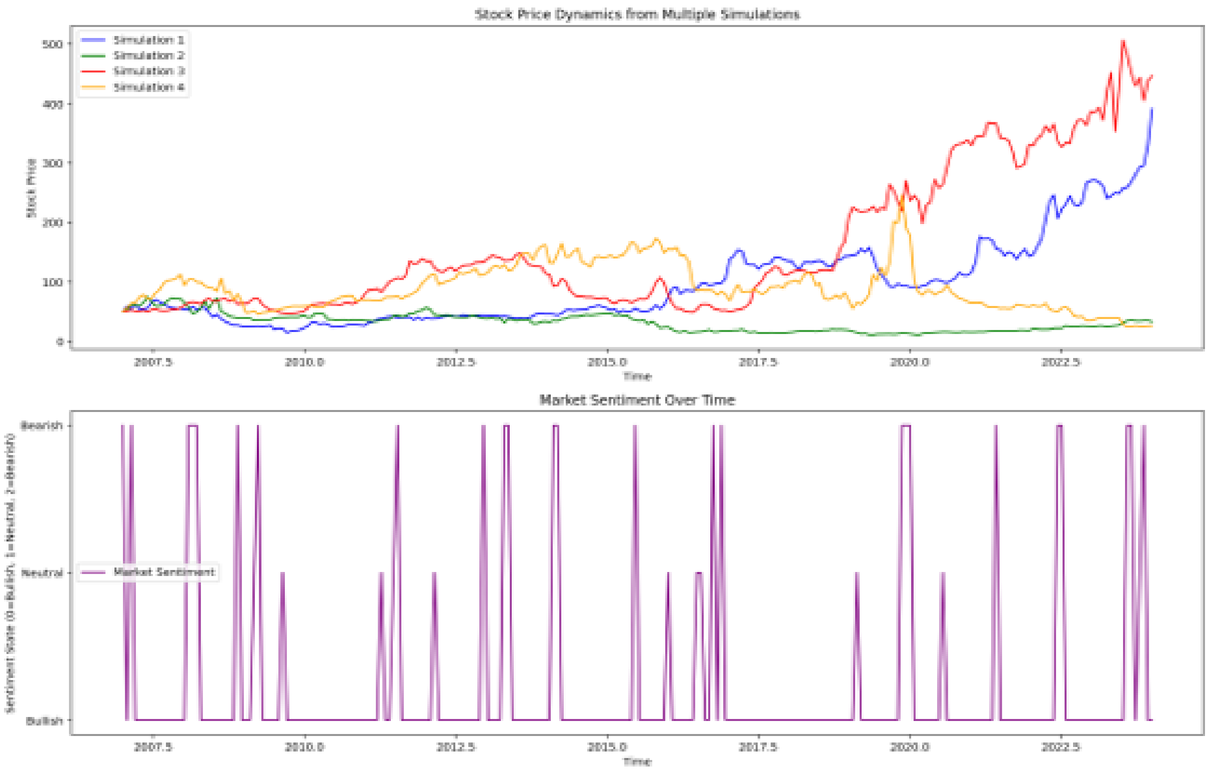

Figure 1: **Stock and market sentiment modelling plot**

For the stock of Exxon Mobil, after multiple trial runs we observed that the market sentiment exhibited frequent transitions between bearish and bullish states, with relatively infrequent movement to a neutral state. This pattern is particularly evident in the oil sector because the market's sentiment was strongly influenced by the overall optimism and caution surrounding global oil prices. During this time, oil prices were rising sharply, and investors in the oil sector, including those invested in Exxon Mobil, were generally more bullish, anticipating high returns due to the global demand for energy and strong market performance. However, when bad news emerged, such as concerns over geopolitical instability, environmental regulations, or sudden drops in oil prices, investors became bearish, showing reluctance to invest and often pulling back from the market due to heightened uncertainty.

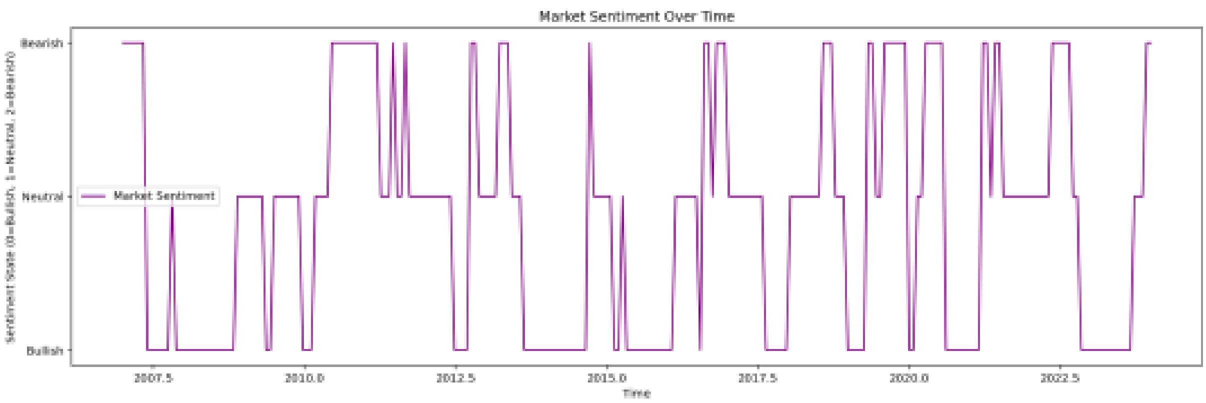

Figure 2: **market sentiment chart**

These frequent shifts between bearish and bullish states, with limited time spent in a neutral state, reflect the high sensitivity of Exxon Mobil's market sentiment to news, particularly in the context of a sector as volatile and tied to global events as oil. This dynamic behavior underlines how news events, whether negative or positive, can rapidly shape investor sentiment and, consequently, stock price movements in the energy sector. **Refer to Figure 2: market sentiment chart**

Moreover, We compared the results of our model to Exxon Mobil's real-life stock performance from 2007 to 2024 and noticed some interesting patterns. In many cases, our model was able to capture similar upward and downward trends seen in the actual stock**(figure 4)**. However, these trends didn't always happen at the same time, likely because of the randomness in the events used to simulate the data. What stood out was that even when the modeled stock took a completely different paths from the real stock, it still ended up with a price close to Exxon Mobil's actual stock price in 2024**(figure 4)**. This was surprising and suggests that while the journeys were different, the overall dynamics of the model led to similar long-term outcomes. We also saw examples where the model closely mirrored real-world stock movements, showing that it could replicate market patterns under certain conditions. That said, the differences in timing, volatility, and price changes highlight how sensitive the model is to the inputs and randomness involved. Overall, while our model isn't an exact predictor of real stock behavior, it gives valuable insights into how market trends might play out over time. **Refer to Figure 3 and figure 4**

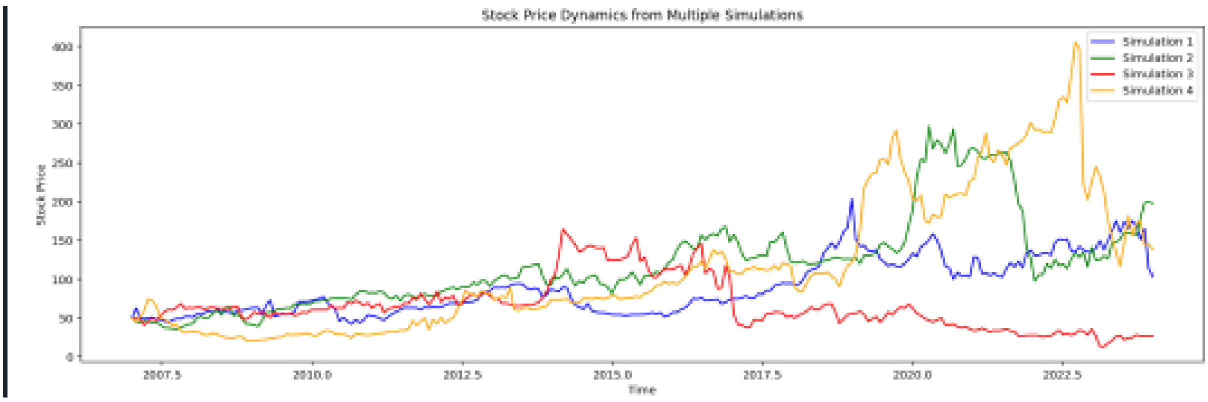

Figure 3: **stock price outcomes from model**

Figure 4: **Exxon mobil stock price**

Learnings in Stochastic Modeling

This project provided key insights into the application of stochastic modeling in financial markets. A major takeaway was the necessity of **jump-diffusion processes** to capture both continuous price fluctuations and discrete jumps caused by news events, which traditional models like Brownian motion fail to address. Transitioning from an **Ornstein-Uhlenbeck process** to the **Heston model** for variance dynamics resolved the issue of negative variance values while effectively modeling market volatility. We also learned the value of using a **Cox-Ingersoll-Ross (CIR) process** to dynamically model jump intensity, allowing the rate of news-driven jumps to align with real-world market behavior. Incorporating a **Markov chain** which was the novel aspect of our model allowed us to simulate market sentiment added a behavioral dimension to the model, reflecting how news affects investor psychology.

Our research revealed that while news plays a major role in shaping market sentiment, as evidenced by the strong correlation between news events and sentiment transitions modeled through a Markov chain, stock price changes are influenced by additional factors like volatility and jump diffusion. These factors are integral to the model's diffusion coefficients and contribute to unpredictable movements in stock prices. For example, even in scenarios where strong positive news signals a bullish market, the stock in our model may still exhibit unexpected drops or rises. This behavior reflects the influence of volatility dynamics, random shocks, and jumps that are independent of market sentiment. The market sentiment graph, however, remains strongly correlated with news events and evolves based on sector-specific sentiment trends derived from historical data. Positive news tends to increase the likelihood of a bullish sentiment, while negative news shifts sentiment toward a bearish state. This dynamic interaction highlights the role of historical trends and sectoral influences in shaping sentiment. Despite this alignment, the divergence between sentiment and stock price movements underscores the complexity of financial markets, where multiple stochastic processes interact simultaneously, creating outcomes that cannot be solely attributed to news or sentiment.

Resources Used

The development and implementation of our model involved a combination of various resources, including academic literature, industry reports, financial data platforms, and specialized tools. Below, we discuss how these resources contributed to the design, calibration, and validation of our experiments and models.

1. News Articles and Event Data

The core of our model was the integration of news-driven dynamics that influence stock prices, volatility, and market sentiment. To capture the impact of real-world events, we relied on news articles that provided insights into sector-specific events affecting companies like Nvidia, Pfizer, and Exxon Mobil. These events were used to simulate how news might impact stock prices and volatility over time.

For example:

- **Nvidia's Q3 Earnings Report and AI Chip Demand:** Articles like the one on Observer provided insights into the technological developments and market reactions affecting Nvidia's stock price, which was then translated into the sentiment dynamics for the Technology sector in our model.
- **Pfizer's Revenue Guidance and Legal Developments:** Articles such as FiercePharma and others discussing Pfizer's COVID-19 vaccine sales and legal cases were used to derive news events that influenced the Health sector. These articles helped simulate the market's response to positive and negative news and informed sentiment probabilities in our Markov chain.
- **Exxon Mobil's Earnings and Environmental Impact:** Articles like ExxonMobil Earnings Report and NY Times regarding Exxon's performance and environmental challenges helped us identify sentiment shifts in the Energy sector.

Refer to Appendix E: News Articles and Event Data for links to the resources

2. Financial Data Platforms and Databases

For accurate parameter estimation and historical data, we used several financial data platforms that offered information on stock prices, volatility, and sector performance.

- **Yahoo Finance (Nvidia, Pfizer):** Provided historical stock prices and volatility data for companies like Nvidia, Pfizer, and Exxon Mobil. This data helped calibrate the initial stock price, variance, and volatility parameters in our model.
- **AlphaQuery and MarketChameleon:** Offered historical volatility and options statistics, which were essential for calibrating volatility parameters (e.g., θ, η) and jump sizes.
- **YCharts and PortfolioLab:** Were useful for additional financial metrics and analytics, which allowed us to confirm the accuracy of the data we used for stock price simulations.

Refer to Appendix C: Financial Data Platforms and Databases for links to the resources

3. Research Papers and Methodology References

To build a sound mathematical foundation for the model, we referred to several research papers and financial literature. Key references included:

- **The Heston Stochastic Volatility Model:** We relied on research from the Heston model simulation in Python to understand the implementation and practical application of stochastic volatility models. This resource provided a guide on how to incorporate jumps in volatility, which was a central part of our model.
- **Stochastic Volatility and Jump Diffusion Models:** Research papers such as those found on MDPI and QuantPy were instrumental in providing theoretical background on the Heston model, stochastic processes, and jump-diffusion modeling. These sources also helped us refine our understanding of how to incorporate market sentiment into our framework.
- **Estimating Option Prices with the Heston Model (Valparaiso University):** Provided insight into the practical calibration of the Heston model using historical options prices, which aided in the calibration of volatility parameters.

These academic resources were crucial for understanding the theoretical aspects of our model, ensuring that we applied well-established methods for modeling volatility and stock price dynamics.

Refer to Appendix B: Research Papers and Methodology References for links to the resources

4. Tools for Calibration and Sector-Specific Insights

Several resources provided insights into sector-specific market behaviors, which were critical for parameter calibration:

- **Nvidia's Financial Reports and Market Trends:** Industry reports like those from Tom's Hardware and Business Insider helped us understand the factors influencing Nvidia's stock performance, which informed the Technology sector parameters in our model.
- **Pfizer and Healthcare Sector Reports:** Articles from FiercePharma and Pfizer's press releases were invaluable for understanding the news-driven volatility in the Health sector.
- **Exxon Mobil's Financial Performance:** We used reports from ExxonMobil's Investor Relations and historical articles from NY Times to analyze Exxon's price sensitivity to news events in the Energy sector.

Refer to Appendix G: Calibration and Validation References and Appendix H: Tools for Calibration and Sector-Specific Insights for links to the resources