(DEEPSEEK FACTS – EVIDENCE FROM THE SELECTED MARKETS)

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Abstract

This research paper focuses on how the introduction of DeepSeek AI in January 2025 affects the stock market in the United States of America, specifically, the companies of the New York Stock Exchange (NYSE) and the Nasdaq. The research utilizes an event study, which is based on a CAPM model, to determine whether the announcement under question results in the abnormal returns that cannot be explained by the normal market risk. The multiple events windows on the day of announcement were used to investigate stock returns of the sampled companies on the day of announcement. CAPM was applied to determine the expected returns and it gave the variance of abnormal returns and cumulative abnormal returns. These results show that the levels of abnormal returns and volatility increases after the introduction of the DeepSeek AI. This means that the market reaction could not have been ideally described using the conventional risk reward models. It was discovered that markets were market specific to AI shocks since technology heavy markets reacted more than diversified markets. Overall, the findings suggest the inefficiency of CAPM under the conditions of technology disruption occurring too rapidly and highlight the part played by event specific and behavioral determinants in the short term market reactions.

Keywords:

DeepSeek AI, Artificial Intelligence, Capital Asset Pricing Model (CAPM), Event Study, Abnormal Returns, Stock Market Reaction, NYSE, NASDAQ.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The financial markets are very sensitive to the information shock particularly those that are technological in nature. The swift development of artificial intelligence (AI) over the past few years has been among the strongest forces of economic trends of the world, corporate strategies, and investor actions. Besides transforming the efficiency of activities in many industries, the emergence of AI technologies has had a significant influence on the capital markets, since it impacts the valuation of companies, the risk attitude, and the future cash flows (Yu et al., 2025). Therefore, any news related to AI innovation can have a major impact on the market, especially in the more technology-oriented stock markets.

Capital Asset Pricing Model or CAPM is among the most popular theoretical models in finance and economics, though it is also used in the analysis of how the market will react and what the investors will expect (Yuan, 2025). CAPM explains the relationship between systematic risk and expected returns and through this relationship, the researcher can determine whether the asset returns are reasonable or because of an abnormality. CAPM comes in handy in such a scenario where there is a big news in the technological front, to determine the normal market returns and the excess or abnormal returns as a result of big events.

This tampered with the global AIs ecosystem in January 2025, when DeepSeek launched a new AI model. On 20 January 2025, DeepSeek officially released its latest AI system and it was perceived as a very powerful competitor to the existing AI platforms and technologies (Peng et al., 2025). The financial market, technology firms, investors, as well as policymakers were all involved in the massive publicity of the news. This launch has reshaped the competitive forces in the technology industry and influenced how the world views the application of AI in its business model as the usage of AI in the business model has increased.

Financial markets began becoming more volatile particularly since 27 January 2025. That was the time of supposed shift in the stock price movements, and especially of AI-related and technology-oriented companies listed on major exchanges in the U.S. New York Stock Exchange (NYSE) and NASDAQ which have a significant level of concentration of firms that focus on technology and innovation had observable fluctuations that matched with the post-launch period (George, 2025). These incidences presented notable queries on the extent to which the launch of DeepSeek AI influenced the performance of the market and whether the returns which were registered was in line with the traditional risk-return assumptions.

1.1.1 DeepSeek AI: Technological and Market Situation.

The artificial intelligence (AI) industry has grown tremendously by 2022, and the advantages of massive language models, deep learning structures, and supercomputers have led to the rapid expansion of the industry across the globe (Mienye and Swart, 2024). In this innovation and competitive market, the emergence of new AI platforms is changing technology companies, financial industries, investment strategy, and share value. The release of DeepSeek AI publicly in January 2025 was also one of the significant developments that led to a massive shift in the AI ecosystem worldwide.

The DeepSeek AI is a massive platform and it will be competing with other major generative AI models like GPT of OpenAI, Gemini of Google, and LLaMA of Meta (Ramachandran, 2025). They are opposed to other tools available in the market, which only focus on very narrow scopes, DeepSeek is being marketed as a very scaleable core model which facilitates natural language processing, data analytics, software development, financial modeling and business intelligence. It is a disruptive alternative to the current infrastructures since the design is aimed at lowering the cost of computation, increasing inference and improving reasoning (Parghi et al., 2025).

Not only was the announcement a technological milestone but it also redistributed competitive power in the AI industry and technology. NVIDIA, Microsoft, Alphabet, Amazon, and semiconductors manufacturers are the main players in the AI value chain; they offer hardware, cloud computing, data centers, and AI services (Zheng, 2025). The appearance of a new player who will be able to alter cost bases, reduce the dependence on the major platforms, or create new demand patterns is of utmost importance considering the profitability, course, and development in the long run.

Regarding investment, AI platforms are general-purpose technologies that can assist in optimizing the achievements of the domains of finance, healthcare, manufacturing, and digital services (Gao and Feng, 2023). Thus, a macro-relevant, and not firm-specific, shock is a new large scale model like DeepSeek. The cause of the market responsiveness is because the shock affects the anticipated cash flows, competitive advantages and systems risk of a huge number of firms.

The launching time was noteworthy. At the start of 2025, the equity markets turned into highly AI-valuation-sensitive. The tech stocks in NASDAQ and NYSE had leaped up under the hope of the AI, cloud computing and demand in semiconductors. Prices already accounted in profits of AI in the future (Nagar, 2025). DeepSeek created a chance and uncertainty: it could become an innovative solution but can also raise competition and reduce the margins and disrupt the established models.

The financial theory proves the fact that such a large-scale news of technological character causes the investors to reconsider the company value and risk. The rate of price incorporation of information in accordance with the Efficient Market Hypothesis thus will be high with situations where the information will be complex, disruptive and impricing and will cause volatility, abnormal returns and interim mispricing in the market (Mcmanus, 2020). These are circumstances that make such announcements the most appropriate to be examined concerning event studies.

DeepSeek was announced on 20 January 2025 with the publicity of financial news, tech analysts, and investors. Consumers in the market took the event differently. Some people viewed DeepSeek as innovation, which would expand and develop the AI economy, hardware, and cloud services. It was viewed by others as the threat which could diminish the power of pricing and destabilize the existing firms. These contradictory expectations provided uncertainties and triggered expediency in the portfolio of the institutional and retail investors (Struckell et al., 2022).

The resultant uncertainty was of increased volatility in the stocks, more so in the firms that were exposed to AI in the NASDAQ and NYSE. This was particularly sensitive to NASDAQ since it has a substantial number of technology and growth oriented firms. Part of the providers of cloud computing, digital infrastructure, and AI-sourced services have also leaked over to NYSE, but this company is more diverse in nature (Liu, 2024). The DeepSeek event was therefore a technological shock across the market and not an industry announcement.

This makes DeepSeek AI an appropriate, economically meaningful event to analyze stock-market responses. It has met the criteria of a core event to be susceptible to financial event-study approach since the introduction was publicly announced on a specific date, which was widely covered by media, and covered a large number of companies. It also offers an experiment in nature, to examine the ability to use classic asset-pricing models, such as the Capital Asset Pricing Model (CAPM), to explain stock returns in a period of technological disruption (Mandala et al., 2023).

The analysis then evaluates the changes in stock prices, but also determines whether they are abnormal returns in some technology and market setting (not only the inflation of DeepSeek event). In this approach, scholars will be able to identify the efficiency of the market and the lack of classical financial theories to deal with high-speed AI-driven innovation.

1.2 Problem Statement

The growing permeation of artificial intelligence (AI) in economic processes has radically transformed the way financial markets information process and value firms. The value of technological innovation in terms of financial economics has long been recognized as a major driver of investor expectation changes, firm competitiveness and market valuation (Schumpeter, 1939; Fama, 1970). Over the past few years, the increased use of AI and digital technologies became a topic of scholarly interest, where researchers noted its role in productivity, the results of innovation, and the performance of firms in terms of their long-term results (Bena and Li, 2014; Brynjolfsson et al., 2018). Nevertheless, the effects of development of AI on the short-run stock prices performance are not well understood at present.

Although that previous literature has identified the connection between technological advancement and stock returns, much of this analysis is based on general trends, including digital transformation, adoption by a firm of technology, or on industry-wide trends in innovation. As a result, empirical studies which can separate large AI product releases as isolated market events are quite scarce. Further, much of the literature that currently exists is either based on descriptive methods or complex econometric methods without clearly basing the analysis on the traditional asset pricing theory. This restricts the option of evaluating the behavior of stock price responses to AI-related announcements as either consistent with anticipated risk-adjusted returns or deviations of the previously known financial models.

Capital Asset Pricing Model (CAPM) is one of the most popular theoretical models of explaining the correlation between the systematic risk and expected returns (Sharpe, 1964; Lintner, 1965; Black, 1972). CAPM, when used with event study approach, becomes a powerful instrument to explore the presence of abnormal returns (AR), which cannot be attributed to market-wide fluctuations, and it is evident that the new information results in such returns (Brown and Warner 1985; MacKinlay 1997). Although it is widely used to cover the corporate events including earnings announcement, mergers, and regulatory changes, it is used very little in assessing the AI product launch events, especially when it comes to the big and high-profiling AI models releases.

Timely and well-specified to fill this research gap is the launch of DeepSeek AI in the open in January 2025. Being one of the largest AI models launches that garnered the interest of international investors and technology-oriented companies, the DeepSeek launch is a distinct information event that can potentially shape expectations when it comes to the potential of future innovations and competitive positioning in the AI sphere, FinTech, and the global technology markets. This incident makes it possible to study the stock market responses in a systematic manner during the day of announcement and during event windows around the announcement day.

Also, financial markets vary in terms of their structural features, industry makeup, and group qualities. The exchanges like NASDAQ and NYSE have different degrees of exposure to technology oriented firms which could result in the heterogeneous reactions to the same technological shock. NASDAQ is typically defined by the increased presence of AI and innovation-based firms, and NYSE also has a more diversified group of companies. According to the prior literature, these differences may affect the inclusion of information into the price (Barberis et al., 1998; Hong and Hu, 2025). However, there is a lack of comparative evidence on the reaction of both exchange-specific and combined-market responses to AI-related events.

Moreover, although the abnormal returns reflect the short term reaction of stock prices to arising information, the cumulative abnormal returns (CAR) will inform on whether the market reaction is short-lived, reversed, or reinforced on the long-term. By studying CAR over a pre and post announcement window, it is possible to understand more about the way investors perceive and adapt to significant technological announcements (MacKinlay, 1997; Kothari and Warner, 2007). The current literature has not sufficiently investigated the existence of continued cumulative impacts of AI product launches on various markets and groups of firms dependent on technology.

It is against this backdrop that the focal research issue that this thesis tries to answer is the lack of a thorough CAPM-based empirical evidence on the impact of a large AI product launch on abnormal and cumulative abnormal stock returns in various stock markets. This paper aims to address this gap by presenting an event study of the DeepSeek AI launch with attention to companies that deal with Artificial Intelligence, FinTech, and Global Technology as listed on the NASDAQ, NYSE, and a combination of NASDAQ and NYSE. Through assessing abnormal returns on the event day and cumulative abnormal returns across different event windows, the study will seek to establish whether market reactions are in line with the traditional asset pricing theory or were abnormal returns caused by non-systematic factors.

In this way, the thesis is directly in defense of the state.

d research questions and hypotheses through a systematic and theory-informed analysis of market reactions to a large AI innovation. It is anticipated that the findings will be added to the literature on financial markets response to technological shocks and will advance the knowledge regarding the way capital markets react to the high-impact AI developments.

1.3 Aim of the Study

The overall point of this thesis is to examine the impact of DeepSeek AI launch on the stock market returns of the United States according to the Capital Asset Pricing Model. The study will focus on establishing the existence of the abnormal returns in the post-launch volatility of the stocks to be considered in the New York Stock Exchange and the NASDAQ when the launch event is present.

The given study will allow estimating to what extent the market responses were influenced by the AI announcement rather than the systematic market risk per se due to the comparison of the CAPM-based expected returns with the observed ones.

1.4 Research Objectives

In order to fulfill the above objective, the study will strive to respond to the following research objectives:

- to investigate the presence of the occurrence of abnormal stock returns (AR) in Artificial Intelligence, FinTech, and Global Technology companies listed on NASDAQ because of the DeepSeek AI launch during the pre-event period, the event period, and the post-event period.
- To test the abnormal stock returns (AR) caused by the DeepSeek AI launch on the NYSE among Artificial Intelligence, FinTech, and Global Technology listed companies in the pre-event, event-day and post-event window.

- To test the hypothesis of whether DeepSeek AI launch caused abnormal stock returns (AR) of the artificially intelligent, FinTech, and Global Technology companies listed on the combined Nasdaq + NYSE sample in the pre-event, event-day and post-event, period.
- To evaluate the presence of cumulative abnormal returns (CAR) of DeepSeek AI launch on Artificial Intelligence, FinTech and Global Technology companies listed on NASDAQ.
- To know, whether DeepSeek AI launch generated cumulative abnormal returns (CAR) to Artificial Intelligence, FinTech and Global Technology companies in NYSE.
- To identify the presence of cumulative abnormal returns (CAR) of DeepSeek AI launch on the sample of Artificial Intelligence, FinTech, and Global Technology listed on the combined NASDAQ + NYSE.

1.5 Research Questions:

Based on the objectives above, the following are the questions of the research in this study:

Research Question 1 (Abnormal Returns – AR)

a) a)Does DeepSeek AI launch produce abnormal stock returns on the event day and in the pre and post event windows of Artificial Intelligence, FinTech, and Global Technology companies listed on NASDAQ?
b) b)Does the DeepSeek AI launch cause abnormal stock returns on the event day and pre- and post-event window to Artificial Intelligence, FinTech, and Global Technology firms listed on NYSE?
c) Does DeepSeek AI launch produce abnormal stock returns on NASDAQ + NYSE-listed Artificial Intelligence, FinTech and Global Technology companies on event day and in event-pre and event-post event window?

Research Question 2 (Cumulative Abnormal Returns – CAR)

a) Does DeepSeek AI launch cause cumulative abnormal stock returns on the event day and during the pre- and post-event window of Artificial Intelligence, FinTech and Global Technology companies that are listed on the NASDAQ?
b) Do DeepSeek AI launches create cumulative abnormal stock returns on Artificial Intelligence, FinTech and Global Technology listed companies on the NYSE on the launch day as well as before and after the event day?
c) Does DeepSeek AI launch produce cumulative abnormal stock returns to Artificial Intelligence, FinTech, and Global Technology companies at the time of launch and within the pre and post event windows on NASDAQ + NYSE?

1.6 Scope of the Study

This study is rather localized as it tends to present an analytical penetration and a clear methodology. Data analysis is based on information about the stock market of the companies that are affected by AI and are listed at the New York Stock Exchange and NASDAQ. The event window shall be based on the DeepSeek AI launch date of 20 January 2025 and volatility period shall be specifically concentrated on the period beginning on 27 January 2025.

The Capital Asset Pricing Model is adopted as the significant methodological framework in the analysis to provide the estimation of the expected returns. Other models of asset pricing, as well as behavioural finance techniques, are excluded since the study will attempt to follow the classical financial theory. The data used is secondary, and it contains historical prices of stock, returns on market indices, and risk free rates that can be used in the financial market of the United States.

1.7 Significance of the Study

This research has been significant to scholarly works and practice of investment analysis in several ways. In theory, the study extends the application of the Capital Asset Pricing Model to the problem of AI-induced disruptions within the market. The research provides the answer to the question on whether CAPM is useful in explaining stock returns during technological shocks, which implies that it provides an insight on the strengths of the conventional asset pricing models in the existing markets that are innovation-oriented.

The study is applicable to investors, portfolio managers, and financial analysts interested in understanding how the major AI announcements affect the performance of the market. When volatility is high, detection of the abnormal returns associated with AI launches can assist investors to enhance their risk management decisions and decision-making, which in turn makes them more useful (Chen et al., 2025).

The study is also applicable to regulators and policymakers as it indicates the systematic impacts of technological innovation on financial stability. As the level of AI evolution is constantly increasing and its influence on economic activity is increasing, the role of AI in capital markets acquires an additional central theme to ensure the efficiency of markets and the confidence of investors.

1.8 Structure of the Thesis

The thesis has been broken down into five chapters. Chapter 1 involves the introduction which provides the background, research problem, objectives, and significance of the research. In chapter 2, the literature review of the subject of AI-driven market reactions, event studies, and the Capital Asset Pricing Model is presented in detail. In chapter 3, the research design including data choice, CAPM computation, and analysis is described. The empirical findings are presented in chapter 4 and the findings analysed with regard to the research questions. The last part of the study will also be chapter 5 that will summarize some of the key findings, implications, limitations, and offer future research directions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction:

The chapter is a literature review and a critical analysis of the academic literature on artificial intelligence, technological innovation, stock-market response as well as asset-pricing models. Given the nature of our research on the effects of introduction of DeepSeak AI on stock-market returns in a Capital Asset Pricing Model, we shall need to take into consideration the theories and the empirical evidence of the correlation between technological shock and market behaviour.

The review offers a conceptualized explanation where the reaction of financial markets to major information events can be understood and the reaction could be explained through the standard asset-pricing models.

It also brings out the relevance of event-study analysis to analyze the abnormal returns and the shortcomings of the previous research that make our research valuable. The chapter puts the prior studies into perspective by summarising the work to give the ground of the context of the analysis on the market impact of the introduction of the DeepSeek AI on the NYSE and NASDAQ.

2.2 Financial Markets and Artificial Intelligence

Artificial intelligence is one of the most drastic forces that are shaping the existing economic and financial systems. The concept of AI can be defined as computer systems that learn, make decisions, predict and solve problems- activities that require the use of human intellect (Korteling et al., 2021). The world of AI is rapidly evolving lately and has reshaped the paradigms of business, the way of how production is conducted, and the competition of numerous business. Investors and financial markets have become sensitive to any AI-related developments and announcements due to the trend of firms relying more on AI (Dzreke, 2025).

In the financial market point of view, AI is seen as a strategic source that may raise profitability, improve performance, and provide long-term value. The economic benefits are effectively realized in the form of cost reduction, enhanced predictions and innovations-driven growth (Ochuba et al., 2024) by the companies that can successfully adopt AI usage. In turn, the news on AI is likely to assume a shift in cash flow and risk in the future and, therefore, make an investor redefine a company. Such re-assessment tends to cause major shifts in the share values and volumes after AI announcements (Chopra and Sharma, 2021).

The financial sector is one of the oldest and the busiest fields where AI is used. The AI technologies influence the algorithms and the high-frequency trading because they demand the machine-learning models to work with the large amounts of market data to come up with the trades within a few seconds (Afua et al., 2024). Another popular use of AI is into risk management, detection of fraud, credit scoring, and optimisation of a portfolio. They ensure efficiency in making decisions, reduction of information asymmetry and market efficiency with the help of these applications. Consequently, not only the specific companies but also the market dynamics and the behaviour of investors at large are becoming affected by the development of AI (Lou et al., 2025).

However, another element that leads to the uncertainty of the financial market is AI-based innovation. The installation of the latest AI systems can be linked to massive development bans, and the question of ethics. The investors may be sceptical regarding the sustainability of AI-based competitive advantages or the possibility of regulation in the future (Gadhoum, 2022). Such uncertainty could make the market more volatile, especially in the short-run, as the players reacted to the news of AI differently. Some investors consider AI announcements as a growth signal whereas others are apprehensive of the announcements because of the perceived risks (Kurter and Bhatti, 2024).

Empirical studies indicate that AI announcements are usually accompanied by the rise of volatility in the price of stocks and abnormal returns, particularly in technological firms (Ante and Saggu, 2025). The exchanges that have high concentration of innovation based enterprises, including NASDAQ, are prone to react to the developments of AI rather powerfully in comparison to the diversified exchanges. This kind of findings means AI innovation is a significant information shock that can cause a transitional shock in the standard market behavior (Al-Harbi, 2025).

2.3 Technology and Change in the Stock Market

The relationship which could be established between technological innovation and stock-market reactions is widely addressed. Innovation is likely to increase productivity, capability, and the value of a firm over the long-term and help companies lower their costs, create new products, and improve their competition (Atayde et al., 2021). Financial markets have seen technological advancement as a way of making profits in the future. The short-term impact of innovation announcement on stocks, however, is dubious, and it depends on how the investors perceive it and what is the situation with the market (Chen et al., 2024).

According to the Schumpeterian innovation theory, new technology creates creative destruction in which a new technology destroys the old industries and replaces the old firm. This redefines forms of the market, and competitive forces. This type of interference is typical in the financial markets whereby the investors reconsider the future of the impacted companies in the abrupt adjustments in prices (Śledzik, 2023). Significant technological announcements are therefore seen as information shock that might play a major role in shaping the expectation of investors, stock returns and market volatility.

The empirical research proves the truth that stock markets are highly responsive to the events of innovation. Abnormal returns are generally observed prior to the product launches, the presentation of patent disclosures, R&D news, and breakthrough technology (Yuan, 2012). Positive abnormal returns are therefore likely to be experienced with such firms that are believed to be leaders in the technology industry due to optimism by investors. However, short-term response is contradictory at least in other works, especially with innovations that are highly uncertain and risky to implement or are untested in their commercial viability (Meissner et al., 2025).

The responses of the market are varied because of several reasons. The firm-specific attributes, which influence investor reactions include size, financial strength and technological capability. The news of innovations is also subject to such forces as the general economic change of mood and instability (Reskiamalia et al., 2025). In addition, it matters what the innovation is like: small-scale ones may receive a weak response, and radical ones may result in massive price fluctuations since they may alter the relationship within the industry (Minniti and Peretto, 2025).

It is important to note that both the market response to technology is unconventional in the risk-return models. Capm Classical asset-pricing models like the Capital Asset Pricing Model (CAPM) posit that the expected returns are only explicable by systematic risk (Majka, 2024). But empirical evidence shows that technological events may produce abnormal returns can be traced to market risk. Consequently, researchers are posing questions on whether CAPM can be useful in explaining the actions of investors where there is a technological break (Rashid & Abdullah, 2023).

2.4 Using the Event Study to Conduct a Financial Research

An event-study method is a financial instrument of external empirical evidence that is widely used in sharing of valuation of the effects of some events on the price of a share. This is based on the

Efficient Market Hypothesis (EMH), at least in the semi-strong form stating that security prices are timely and correct with respect to the different market information that is publicly available (Alkali et al., 2022). By so doing, any new news, whether it be, corporate news or technological news, must be applied onto the stock prices in an almost instantaneous fashion (Kamal et al., 2022).

The main aim of an event study is to find out whether the event that has occurred has reflected stock returns, which are not normal and are in contrast to the normal market behavior. It is done through identification of the event date and creation of an event window, which surrounds the event date to capture the market reaction before the event and the reaction after the event (Eden et al., 2022). An asset-pricing model is applied to compare the expected returns and the actual returns. Deviation of the actual and the expected is the abnormal returns that is the response of the market to the event (Hai and Khoa, 2025).

The event studies can be used in the majority of the financial fields. They are applied by the scholars to assess the effects of mergers and acquisitions, earnings announcement, changes in dividends, regulatory action, announcement of macroeconomic news, and technological innovation (Ghoul et al., 2022). They may be very flexible and efficient as shown by their extensive application to determine the impact of discrete events on the financial markets. As of a more recent date, event studies have touched the response of the market to a news of innovation, such as a contribution to artificial intelligence and online technologies (Bao et al., 2024).

The fact that it is possible to control the overall market trends is an important advantage with event-study approach. The researcher can determine the impact of events on the market rather than the general trends of the market through the application of the expected return models like the Capital Asset Pricing Model (Corrado, 2010). This makes event studies especially relevant in constructing the analysis of the AI announcements that occur between the volatility of the major markets. The study opts to use the event-study approach to establish whether the event index DeepSeek AI launch was producing abnormal returns above those induced by the systematic market risk.

Event-study methodology has the above strengths, but has certain limitations which are worth noting. The results can be considerably altered with the estimation period and event window. Small event window can also miss the market response that is delayed yet broad window can have the unrelated data to the analysis and may thus as well be polluted (Oler et al., 2008). Moreover, in a case where two events are overlapping, chances are that the impact one event has can be watered down. Noise of the prices of the market and sentiment of the investors and other economic conditions of the market can also influence the stock prices during the event period hence making it difficult to interpret.

The other limitation is in respect of the choice of the expected return model. Different models can arrive at different estimates of abnormal returns. However, this does not mean that the CAPM is the least applied model in event studies because of its simplicity and theoretical background. CAPM is a well-mastered, straightforward standard of the anticipated returns in the experimental research of the finance research, yet some more intricate models exist (Elbannan, 2015).

2.5 Capital Asset Pricing Model (CAPM)

2.5.1 Overview of CAPM

One of the most important and popular models of the current finance is Capital Asset Pricing Model (CAPM). It was first developed by Sharpe, Lintner and Mossin (Kumar et al., 2023). CAPM is a model that associates the future returns of a given asset, and its exposure to systematic risk in the market. The model is hinged on the fact that the time value of money and the market risk that cannot be avoided should be offset on the investors. CAPM holds the that only the systematic risk that is the risk that cannot be diversified is compensated with higher expected returns.

CAPM is the model where the anticipated returns of an asset are linked with a linear relationship of its beta. Beta refers to the responsiveness of returns that an asset is exposed to in the event the market is undergoing overall changes (Faiteh & Aasri, 2022). The expected return is calculated with the help of the given formula:

$$E(Ri) = Rf + \beta i\ (Rm - Rf)$$

Where:

- *E(Ri)* is the expected return on asset *i*
- *Rf* is the risk-free rate
- *βi* is the beta of asset *i*
- *Rm* is the expected market return

E (Ri), in this instance, refers to expected correction of an asset, Rf refers to returns of risk-free asset, 8i refers to the systematic risk of asset, and (Rm Rf) refers to the market risk premium. The model explains that the most returns are likely to be realized by the assets that have high beta to compensate the investor as high assets are more exposed to market risk.

CAPM has been a fundamental aspect of financial decision making and studies among scholars. It is widely used in the management of portfolios, estimate of the cost of capital, performance evaluation and risk evaluation. Even though newer and more advanced theories of how to price an asset have been developed, CAPM still remains a reference point because of its theoretical simplicity and application usefulness.

2.5.2 Assumptions of CAPM

CAPM also possesses several simplifying assumptions which make the theory manageable. The key assumption is that, the investors are risk-averse and rational and desire to get the highest possible expected utility. The model is also built on the same coin, holds the expectation of all investors being homogenous with respect to the returns of the assets, variances and covariance (Chen, 2021). It means that investors use the same information base and interpret information in the same way.

CAPM is also a frictionless market: taxes, transaction costs as well as short selling do not exist in markets. There is complete freedom of borrowing and lending money to investors at one standard risk-free rate. It also presumes that the assets are fully divisible and publicly traded and as such provides a chance to investor to construct fully diverse portfolios (Perold, 2004).

Even though the assumptions have been criticized as being unrealistic, there are helping in giving a simplified means of knowing the relationship between risk and risk-return. In fact, anything that contradicts these assumptions can weaken the power of CAPM. Nevertheless, the model has remained to be vastly applied in empirical studies because of its simplicity, ease of interpretation, and a good theoretical foundation. We can use it as a standard by which other models of the asset-pricing are evaluated.

2.5.3 CAPM in Event Studies

CAPM is also prevalent in event study methodology to quantify the expected returns, and also to identify abnormal returns around specific events. CAPM calculates the normal (expected) stock returns based on the systematic risk of the stock and the market in general (Xie, 2023). After this, case realized returns during the event window are compared to CAPM based expectancy returns to determine the abnormal returns.

The outcome of event studies is the implementation of CAPM to enable the researcher to separate returns, which happen as a result of general market movements and returns as a result of revelation related to this event (Teall, 2022). In case the abnormal returns are observed to be material, then this is the clue that the incidence had a bearing in the stock prices more than what would have been predicted by market risk alone. It comes in especially handy in the context of the analysis of technological announcements because in the latter case, the responses that may be caused by the event can be inspired by atypical risk-return patterns.

There are empirical studies that employed the application of CAPM in event studies, which examine market reaction to event of innovation like introduction of a new product, technological revolution, and structural change in the market (Qin, 2024). Though some studies show that CAPM may be applicable and successful to explain returns during the event, there are other studies that show that there will never be no abnormal returns that show that investor behavior in the event of a technological change during a rapid change may not be explained on the basis of the assumptions of the CAPM (Zhang, 2019).

2.6 Empirical Evidence on Market Shocks and Innovation

Empirical research on the relationship between stock market performance and events of innovation provides mixed or even situation-specific results (Atalay et al., 2013). A lot of the literature shows that the high scale communications of innovation have been known to generate positive abnormal returns signifying hope in future development, development in productivity and competitive benefits by the investors (Chu et al., 2023). Empirical studies on the topic of new products release, patents, and technological breakthroughs tend to show short-term increases in the price of the stock, particularly when the company is regarded as a technology innovator (Schaminée, 2021).

However, there are other empirical studies that focus on the role of uncertainty regarding the change in technologies. The outcomes of the events surrounding innovation are typically poorly defined, including the prohibitive cost of development, the level of uptake that is hard to predict, regulatory concerns, and potential disruption of existing business models (Han et al., 2023). As a result, markets are able to respond to this through volatility rather than sustained good returns.

According to other scholars, negative or statistically ineffective abnormal returns following the announcement of innovations are recorded, which indicates a conservative approach of the investors towards the unknown or disruptive technologies (Saranj & Zolfakhari, 2025).

More indications of abnormal return behaviour include the fact that market shocks related to structural change provide greater information on the topic (Savor, 2012). The research on indexes recomposition may demonstrate that index composition changes can generate non-explainable abnormal returns using traditional risk factors. These returns have largely been attributed to changes in the investor demand, liquidity changes and information flow changes (Sohail et al., 2012). Although the events of recomposition of the indexes are not comparable events like the events of AI-related announcements, both are structural market events capable of interrupting the pricing mechanisms in the short term and leading to an aberration of the expected returns according to the asset pricing models (Zhu, 2025).

Market structure and investor composition have also been found in the research of market responses of innovation through empirical studies (Che and Chen, 2024). Technology oriented market is more likely to respond shock due to innovations as potentials of increase are greater and the impact of disruptive technologies felt is greater (Ganotakis et al., 2023). Research related to the subject of digital transformation and AIs adoption has shown that news related to artificial intelligence can be predisposed to lead to a sharp reassessment of the worth of companies that belong to the industries having a direct connection with the revenue prospects and cost reduction of artificial intelligence (Gao et al., 2025).

The recent empirical research on AI-related phenomena could suggest that markets are extremely sensitive to major AI developments, such as, but not limited to, machine learning breakthroughs, large-scale introducing AI products, and strategic AI investments by major businesses (Wilson et al., 2024). These types of reactions are more likely to be more intense in exchanges that are highly technologically focused such as NASDAQ compared with the less technologically focused market. It has been also argued that AI announcements have the potential to generate abnormal returns, which may persist even when the corresponding event occurs, and the expectation regarding the anticipated change in investor expectations is deemed to be long-run in nature (Chen et al., 2022).

Despite the increase in the existing literature on the topic of innovation and market shock, relatively little literature applies classical asset pricing models, such as the Capital Asset Pricing

Model, to examine the short-term market reaction to AI-driven events (Li, 2025). The bulk of research has been predetermined by descriptive analysis or highly advanced econometric techniques without being founded upon the classical financial theory. The gap in the literature is whether other abnormal returns that have been experienced during the innovation shocks are due to systematic risk or whether they are an anomaly to the expectations of the CAPM. The current research is able to bridge this gap with a CAPM-based event study framework to find out the effects of DeepSeek AI launch on the market.

2.7 Market-Specific Responses: NYSE vs NASDAQ

The financial markets differ in their structural attributes, firms composition, and investors behaviour that could lead to them responding differently to the events that are founded on innovation. Another big stock exchange within American profile is the cases of New York Stock Exchange (NYSE) and NASDAQ. NYSE has long been associated with large and well-established businesses in the entire range of industries, including the manufacturing sector, finance, healthcare, and consumer goods (Yeught, 2006). As a matter of fact, NASDAQ is a growth and innovation-based concentration which is high-tech.

These structural differences have huge implications of the sensitivity of each market to technological external influences. High technology markets such as NASDAQ would be more sensitive to such announcements that are related to innovations because it has increased exposure to areas that directly depend on the technological change (Davidovic & McCleary, 2025). The investors in the company listed in the NASDAQ have a higher growth orientation and would respond more to information that might reflect future technological dominance or even an increase in competitiveness. The announcements that concern innovation, as a result, have greater likelihood of producing substantial price variation and abnormal returns in such a stock exchange as NASDAQ.

The practical study helps to confirm the hypothesis that the structure of a market is highly significant in shaping the reaction to the news about technology. Research has established that technology oriented trades are more unstable in the event that innovations have been announced in comparison to diversified markets (Farea and Aljofi, 2025). This instability is an expression of the heightened demands of the investor and doubt regarding the long term impacts of the new technologies. Quite on the contrary, there are other markets such as NYSE that may also respond moderately due to greater spread diversification and percentage of value oriented companies (Cadena-Silva et al., 2025).

Investor behaviour is also different with respect to exchange behaviour. It has a greater share of institutional traders, venture funds and speculative traders in the form of NASDAQ who are not afraid of the exposure to high growth technologies (Zhang and Wang, 2024). This investor base can lead to improvements in the market reaction to announcements on AI and generate more significant abnormal returns and volatility. On the other hand, the investor base of NYSE is relatively more conservative and that might cause slower or less significant price adaptations to take place in the aftermath of events that are inspired by innovativeness (Roe, 2020).

The beneficial information concerning the fact whether the influence of the large AI event is appropriate to all markets or it is conditioned by the organizational factors will be the comparative analysis of the market-specific responses. When the DeepSeek AI launch delivered rather unrelated abnormal returns in NYSE and NASDAQ, it would mean that market structure and the investment behavior of the investors are of utmost significance in mediating the effects of technological shock (Cui et al., 2025). Conversely, similarity of the response to the two market would imply that it was a market wide event.

The reaction of NYSE and NASDAQ to the comparison, in its turn, allows the researcher to comprehend the way in which innovations made possible by AI could affect different areas of the financial market. This paper carries out an analysis to show whether the differences in returns that are observed between the two exchanges are accounted by systematic market risk or are abnormal market specific responses. This kind of comparison makes the analysis more sound, as well as it helps to introduce the piece of literature concerning the innovation, efficiency on the market, and asset prices.

2.8 Research Gap

Despite the fact that many researchers have conducted research on the technological innovation, event-study, and the Capital Asset Pricing Model (CAPM), not much has been done to combine all the three to discuss the market shocks caused by artificial-intelligence (AI) in a standard asset-pricing model. The new research papers on technological innovation tend to be more preoccupied with the long-term firm performance, productivity progression or strategy outcomes. More frequently, though, short-term market reactions are explored by descriptive statistics or complex econometric specifications, and not by standard finance theory.

Although event-study design has gained some popularity in determining the impact of the corporate and macroeconomic events, not many studies have estimated using the CAPM-based expected returns to estimate the impact of the innovation-driven shocks and especially the AI-related shocks. Most empirical analyses of AI announcements consider an outcome of the firm level, or the sentiment of investors, without explicitly aimed at estimating whether the returns that are observed are in line with CAPM or are abnormal returns in addition to systematic company risk.

Little empirical studies also exist that pay attention to AI product launches as a one-time occurrence in the market. In the vast majority of studies, the overall tendencies of the digital transformation, or the use of AI are investigated in the long term and not the immediate consequences of the specific AI implementation. This lack of event-based analysis is harmful to our understanding of the immediate response of the financial markets to the big AI innovations and is the response different in different market structures.

The other area that has not been explored is a comparative analyzing of different exchanges. There are only very few research on the reaction of different stock markets to the same technological shock. The rebuilding of the two markets is the reason behind the more comprehensive insight into the way the market composition and the behaviour of investors can be conditional on the responses to the events provoked by the AI because of the structural differences between the New York Stock Exchange (NYSE) and NASDAQ.

The paper is addressing these gaps in the literature by applying event-study design based on the CAPM, which will evaluate these short-term stock market impacts of the introduction of DeepSeek AI on January 2025. The work, which is based on the evaluation of market feedback on the NYSE and NASDAQ and is used to fill the gap in the literature that discusses asset pricing, technological innovation and financial market behaviour and to determine the relevance of CAPM to the era of the swift technological disruption.

2.9 Chapter Summary

The selection of literature reviewed in this chapter was extensive insofar as it was selected based on the research topic since it dealt with artificial intelligence, technological innovation, stock market response, event-study methods, and the Capital Asset Pricing Model. As it has been revealed in the review, AI has become a transformational tool that influences the performance of the firms, their expectations towards investors, and the market dynamics in general. Previous research has unanimously found out that radical technological innovations are termed as information shock, which causes an observable change in the market volatility and stock prices.

The review also surveyed empirical results on the market response to innovation events to the process, but found conflicting results on the trend, the magnitude of the abnormal returns and their sustainability. Whereas some of the market research findings provide encouraging market results with a tendency to positive investor reaction, others inform of the growth of skepticism and instability after the news on technology. The presence of these contradictory results indicates that the process of innovation reaction in the market is complex and does not always conform to the traditional risk-reward paradigms.

In addition, practical uses and theoretical framework of event-study techniques and the CAPM were covered in the chapter. As much as CAPM might be regarded as one of the most prevalent asset-pricing models, the literature shows that the explanatory power of the model is bound to decline as soon as rapid technological developments and market shocks, and activity in the field of AI take place.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Chapter outlines the approach that was used to conduct the research on the effect of DeepSeak AI introduction on the U.S. stock market returns. It explains how the objectives of the research shall be translated into practical activities and data analysis to provide responses to the research questions. The financial aspect of the study suggests that the study is model-driven, quantitative, which is objective, reliable and consistent with the basic financial theory.

The research question is whether DeepSeek AI is not a significant event in the market on January 2025 to cause an abnormal stock return on the January effect, other than returns caused by systematic market risk. It uses event-study methodology that is backed by Capital Asset Pricing Model (CAPM). This is how to separate normal performance in the market and the one that will immediately react to the introduction of the AI.

The chapter talks about the general research design in which the event is chosen, sample is chosen, data is collected, event and estimation windows are determined, returns are calculated and expected returns are estimated using CAPM, abnormal returns are measured, hypothesis is set and analysis tools used. The research has strength, repeatability and empirical finance criteria through theory-coherent approach.

3.2 Research Philosophy

The study is prejudiced towards positivist philosophy as per which the actions of the financial market can be quantified based on the objective information and mathematical models. When the subjects of the financial researches are concerned this methodological approach has been suitable, as in terms of financial metrics, e.g. prices, returns and risk, these values can be measured and relied on testing.

The approach to use is a quantitative one, which relies on numbers, statistics, and mathematical models to compute how the market would respond (Apuke, 2017). The approach helps in the testing of hypotheses, a cross-market test, and objective testing of abnormal returns.

This is a deductive study the hypotheses are formulated on the current literature and finance theory. The hypotheses regarding the abnormal market action after the DeepSeek AI debut are tested with the help of the CAPM theoretical framework and the event-study design.

3.3 Research Design

The research uses an explanatory study design in order to establish causal relationships between the introduction of DeepSeek AI and stock market performance. The design helps in determining whether the developments of changes in returns have been caused by certain events and not by the unpredictable market changes (Mills et al., 2010).

The event-study designs analyze the price responses of share values to new information, the nature of which is of value relevance. Finance Event studies are an evaluation of the market efficiency and investor reaction to announcements in the market such as merger, earnings, alterations in regulation and technological advancements (El Ghoul et al., 2022).

According to the model, the CAPM is applied as a standard of the anticipated returns. The analysis of the actual versus the CAPM-expended returns will eliminate the abnormal returns caused by the launch of the AI. This will enable the study to test whether the market responsiveness is in tandem with the traditional risk-reward theory or otherwise due to innovation shocks.

The study is an integration of time series analysis, which entails examination of the pre and post event returns and cross-sectional examination of the reactions of the various companies and in addition a comparison of the reactions of the NYSE and the NASDAQ. The explanatory strength and strength is boosted through such a two-sided approach.

3.4 Event Identification

The formal release of the DeepSeek AI model on 20 January 2025 is no longer the focus of the study, but the main event. It was chosen because it was one of the major technological events, which rocked the whole AI industry, technological corporations, and investors. It was a self-evident information shock that was popularized by the media and was talked of in the financial and tech circles.

The event meets the event-study criteria i.e. a definite date, an announcement to the market, and a likelihood of altering the expectation of the investors in terms of profitability in future, competition, technology leadership.

The market statistics show that since 27 January 2025, the market is volatile and therefore it is a bit behind schedule until the market is fully adjusted. This kind of laggard is typical in cases where investors have the need to digest complex technological information. The delay identification enables the study to get short and immediate results.

Analytically, the time of event is T= 0, 20 January 2025. Days that the trading is conducted during and around this date are studied to gauge how the market is going to respond before and after the launching day.

3.5 Sample Selection

The sample includes the NYSE and NASDAQ-trading companies that are related to technology and artificial intelligence. They chose those companies due to direct or indirect involvement in AI, such as AI development, cloud computing, semiconductor production, data analytics, and digital infrastructure.

This would enable the inclusion of both NYSE and NASDAQ to compare the market specific responses. NASDAQ is also extremely vulnerable to AI developments because it has several growth-oriented and technology firms. NYSE has greater diversification of the new and old segment. This comparisons act to test the market structure effect on the size and significance of abnormal returns.

To retain the quality of the data only firms that constantly trade and possess enough past prices data were taken into consideration. Stocks that lacked information and very low liquidity and odd time trades were removed. The screening reduces estimation and increases the precision of returns and beta estimation.

3.5.1 Market Classification and Sample Firms

The sample involved in the study is an intensive sample of 28 AI related and technology intensive companies. All of them are traded on the NASDAQ or NYSE and are chosen because of their direct activities in the sphere of artificial intelligence, semiconductor fabrication, cloud computing, and digital infrastructure and AI-enabled services. The availability of both exchanges with firms will allow to compare technology oriented NASDAQ and the less concentrated NYSE.

The CAPM expected returns estimation, actual returns and subsequently the abnormal returns (AR) and cumulative abnormal returns (CAR) analysis of the sample firms was done. Such calculations did not leave out any of the firms and guarantee the consistency and completeness of the methodology.

All the sampled firms, stock ticker, and market classification, and standardized risk-free rate used in the analysis period are listed in Table 1.

Table 1: Sample Firms and CAPM Inputs

Sr.	Company Name	Stock Ticker	Exchange	Market Ticker	Risk-Free Rate (U.S. 10Y, Early 2025)
1	NVIDIA Corporation	NVDA	NASDAQ	NASDAQ	4.53%
2	Broadcom Inc.	AVGO	NASDAQ	NASDAQ	4.53%
3	Advanced Micro Devices	AMD	NASDAQ	NASDAQ	4.53%
4	Microsoft Corporation	MSFT	NASDAQ	NASDAQ	4.53%
5	Alphabet Inc.	GOOGL	NASDAQ	NASDAQ	4.53%
6	ASML Holding	ASML	NASDAQ	NASDAQ	4.53%
7	Micron Technology	MU	NASDAQ	NASDAQ	4.53%
8	Vertiv Holdings	VRT	NYSE	NYSE	4.53%
9	Constellation Energy	CEG	NYSE	NYSE	4.53%
10	Taiwan Semiconductor	TSM	NYSE	NYSE	4.53%
11	Marvell Technology	MRVL	NASDAQ	NASDAQ	4.53%
12	Qualcomm	QCOM	NASDAQ	NASDAQ	4.53%
13	Super Micro Computer	SMCI	NASDAQ	NASDAQ	4.53%
14	Equinix	EQIX	NASDAQ	NASDAQ	4.53%
15	Vistra Corp.	VST	NYSE	NYSE	4.53%
16	Dell Technologies	DELL	NYSE	NYSE	4.53%
17	Intel Corporation	INTC	NASDAQ	NASDAQ	4.53%
18	Tesla, Inc.	TSLA	NASDAQ	NASDAQ	4.53%
19	Apple Inc.	AAPL	NASDAQ	NASDAQ	4.53%

20	Meta Platforms	META	NASDAQ	NASDAQ	4.53%
21	Amazon.com	AMZN	NASDAQ	NASDAQ	4.53%
22	Oracle Corporation	ORCL	NYSE	NYSE	4.53%
23	Applied Materials	AMAT	NASDAQ	NASDAQ	4.53%
24	KLA Corporation	KLAC	NASDAQ	NASDAQ	4.53%
25	Lam Research	LRCX	NASDAQ	NASDAQ	4.53%
26	Cisco Systems	CSCO	NASDAQ	NASDAQ	4.53%
27	Skyworks Solutions	SWKS	NASDAQ	NASDAQ	4.53%
28	Qorvo	QRVO	NASDAQ	NASDAQ	4.53%

3.6 Data Sources

The study utilizes only secondary data that would be suitable in the research of the financial market. The secondary data gives objective information on the results of the market and makes it possible to repeat the results.

The following data were used:

- The stock values of the NYSE and NASDAQ corporations under analysis were retrieved on a daily basis as a close value.
- The index values of the market that represents the overall performance of the market on a daily basis.
- Short-run risk-free U.S. Treasury bills.
- To co-ordinate returns, institutional trading calendars.

The statistics on prices and indexes were retrieved in any of the reputable databases, e.g., Yahoo Finance, Bloomberg, or some other one. All the data were to be adjusted in order to provide a unified setting of data in these intervals of time through dividends, stock splits and other corporate measures.

3.7 Estimation Window and Event Window

Proper estimation and event windows are the most important aspects of an event study as they directly affect the reliability of estimation of expected returns and the calculations of abnormal returns. This piece has developed two windows that are specified to give the impression of the DeepSeek AI release and the absence of any encroachment by other market forces.

3.7.1 Estimation Window

The estimate window is also used in recording the aberrant behavior of returns, as well as in calculation of beta coefficients of capital asset pricing model (CAPM). It must be placed completely before the event window in a manner that the event does not have an effect on the estimates.

This research has a period of estimation of 120 trading days before the event period. This is the empirical finance norm and provides adequate data to approximate stable betas on the basis of regression. It also minimizes the impact of short term fluctuations and noise in the markets that could not be biasing the parameters.

By doing this, the returns provided by the markets do imply the normal market performance, without the speculation relating to the DeepSeek AI release, by selecting a pre-event period. This increases the validity of calculations of the abnormal returns and interpretation of the finding.

3.7.2 Event Window

The event window will be used to monitor the stock prices as a reaction to the DeepSeek launch of AI. The potential investor responses could be realized before, at the time of announcement or after the announcement and hence, more than one event window would be applied to observe the different event patterns of market reaction.

The windows under analysis are the following:

- [-8, 0] Trading days, Deepseek Event Pre Market Reaction.
- \{\|human|>[0, 0] Deep seek Event Trading days.
- [0, +8] The number of trading days, analysing post-announcement after Deepseek Event.

The reason is that there is no anchoring of results to a single specification through the use of multi windows hence rendering the analysis more stable. It also allows us to see the length of the abnormal returns that are either temporary or can persist even after the initial announcement- which is important in case of AI events whereby the investors need time to process complicated information.

3.8 Measurement of Returns

It has been decided to use the logarithmic returns to compute the daily stock returns. There are advantages of using logarithmic returns in a financial study since it accumulates returns over a given time and skewness abnormality. They work well especially in day to day event studies.

The following is the formula of stock returns;

$\mathbf{R}i\mathbf{t} = \ln(\mathrm{P}i\mathbf{t}/\mathbf{P}i\mathbf{t}{-}1)$

Pit denotes the closing price of stock i on day t, where Rit is the movement of the stock i in day t that is, the return of the stock on that day, and Pit 1 is the closing price of the stock in the previous trading day.

The computation of market returns are done under the same logarithmic calculation with regards to market index. The fact that the individual stock and the index were also calculated using a uniform calculation also implies that the estimation CAPM will be comparative and sound.

3.9 CAPM-Based Expected Returns

The estimation of the prospects of returns is undertaken using the CAPM by estimating the anticipated returns in an equivalent manner as to the systematic market risk. CAPM is a theoretical model of normal returns benchmark, and has been widely used in event studies.

CAPM equation may be presented as follows:

$E(Rit)=Rf+\beta i(Rmt-Rf)$

Here, Rf i is the risk-free rate of return, R mt i is the market day t of stock i and 2i i is the systematic risk of stock i in the market.

This model is that investors will only be rewarded with the process of taking a systematic risk; risk that is not systematic can be simply diversified away. CAPM will help in dividing the returns in the market and the ones associated with the introduction of DeepSeek AI application in the study.

Table 1 has estimated the expected return of the 28 firms, as per the CAPM. The calculation entailed firm specific beta estimates with an estimated period of 120 days. The risk-free rate was applied consistently in the form of the U.S. 10-year Treasury yield that was about 4.53 percent at the start of 2025. Afterwards we computed both abnormal returns and cumulative abnormal returns, in each firm. The market-level results are not just an average of the sample but a sample.

3.9.1 Beta Estimation

The estimation of the beta coefficient is performed by the ordinary least squares regression over the estimation window. The assumption will be the following regression:

Rit=αi+βiRmt+ϵit

In which, alpha i is the intercept, beta i is the responsiveness of stock returns to market movements and εit is the error.

The beta is calculated and represents the sensitivity of a given stock towards the systematic risk and is used to determine the expected returns as a result of the event during the period. Good estimation of beta is significant as it directly affects estimation of abnormal returns.

3.10 Abnormal returns and Cumulative Abnormal returns

The difference between actual stock returns and the expected returns as the CAPM calculated are calculated using the abnormal returns. They are calculated as:

ARit=Rit−E(Rit)

The positive abnormal returns indicate that a stock performed better than expected in consideration of its level of market risk and a negative abnormal returns is an abnormal underperformance.

The cumulative abnormal returns (CAR) may be applied to quantify the total impact of DeepSeek AI launch in the long run; that is, cumulative abnormal returns across the event period:

$$CAR_i = \sum_{t=T_1}^{T_2} AR_{it}$$

CARs also show the relevance of the event to the economy, as they describe the performance of numerous trading days, which are abnormal.

3.11 Hypothesis Development

The following hypotheses will be taken into consideration in the research due to the literature review and study objectives:

Abnormal Returns (AR)

- H1a: DeepSeek AI launch had a negative and statistically significant negative abnormal returns on AI, FinTech and Global Technology firms on NASDAQ.
- H 1b: The launch of DeepSeek AI did create negative and statistically significant abnormal returns of the AI, FinTech, and Global Technology firms listed on NYSE.
- H1c: There were negative and statistically significant abnormal returns of AI, FinTech, and Global Technology firms on the combined NASDAQ + NYSE sample associated with the launch of DeepSeek AI.

Cumulative Abnormal Returns (CAR)

- H2a: The DeepSeek AI had negative and statistically significant cumulative abnormal returns on AI, FinTech and Global Technology companies that were listed on the NASDAQ.

- H2b: DeepSeek AI launch created negative and statistically significant cumulative abnormal returns to AI, FinTech, and Global Technology listed on NYSE.

- H2c: There were negative and statistically significant cumulative abnormal returns to AI, FinTech and Global technology companies listed in the combined NASDAQ + NYSE sample.

These theories make it possible to scientifically evaluate the efficiency of the market, the asset pricing theory and market-specific responses to technological innovation.

3.12 Data Analysis Techniques

The summary of the behavior of the returns is summarized as the descriptive statistics. Then, it calculates mean abnormal returns and cumulative abnormal returns within each event window. The comparison of NYSE and NASDAQ indicates the differences that are peculiar to market.

Statistical significance is conducted using t -statistics and p -values in the conventional confidence levels to make any conclusion with solid evidence.

3.13 Ethical Considerations

The study is based on any secondary data open publicly and also there is not human subject and confidentiality in the research. Correct citation, open methodology, and correct reporting of outcomes are some of the guidelines used to consider the moral academic guidelines (Tripathy, 2013).

3.14 Chapter Summary

In this chapter, the author described the research design that will be used in the study to determine the effects of the launch of the DeepSeek AI in the returns of the U.S. stock market. The framework was structured in a manner that it guarantee analytical rigour, objectivity and best established empirical practices in finance. The analysis was a blend of event-studies with the Capital Asset Pricing Model (CAPM), which designed a systematic way of isolating the influence of AI launch in the market and the general tendencies in the market.

It has given the research design, identification of events, choice of sample and sources of data to be used. The opportunity to contrast the responses of both markets to the introduction of DeepSeek AI was realized through the concentration on the firms that were related to AI on the New York Stock Exchange and NASDAQ. Specifications of the estimation period and several event windows proved helpful in getting the right beta estimates and quality measurement of the market responses before, during, and after the launch.

Stock returns computation, estimation of the expected returns using the CAPM, the abnormal returns and cumulative abnormal returns were also explained. These actions form the empirical foundation of finding out whether the changes of price were founded on systematic market risk, or on the abnormal returns founded on AI announcement. Hypotheses were applied in the research to test the abnormal returns, and changes in market volatility and capacity of CAPM to explain returns in the case of technological disruption.

Chapter 4: Findings and Analysis

4.1 Introduction

This chapter reports the empirical results of a research conducted on the effect of the launch of DeepSeek AI according to January 2025 on the stock market performance of the United States. The event-study model was applied on a Capital Asset Pricing Model (CAPM) basis and we chose all the 28 AI based companies which were publicly listed on NASDAQ and NYSE and were found in Chapter 3.

I have obtained the expected returns computed using CAPM, actual returns and abnormal returns (AR) and Cumulative abnormal returns (CAR) over a set of event windows in each of the cases of a firm. The market level findings of the chapter summarize and average the whole sample, and we mention some of the sampled firms to elaborate on our findings. The plan will make the analysis very comprehensive and easy to follow.

The chapter takes into consideration its abnormal returns, cumulative, and volatility changes, firm-specific deviations to the CAPM and market-specific responses in order to know whether returns in the DeepSeek AI announcement were substantially different in CAPM predictions.

4.2 CAPM estimation and the calculation of expected returns

CAPM was applied on the 28 sampled companies to give an approximation of the expected returns on the stock during the event window of the DeepSeek AI launch. Ordinary least squares (OLS) regression was employed in estimating firm specific beta coefficients during a 120 day pre event estimation period to ensure that beta coefficients represented proper normal market functioning and not due to the given event.

I considered the 10-year Treasury yield of the U.S. (approximately 4.53 percent in early 2025) as the risk-free rate of all of the firms. The market returns that were reported on a daily basis were obtained on the market index of each of these companies either on NASDAQ or NYSE. The expected returns of CAPM were employed to make a parallel in the calculation of abnormal returns, which could only be explained as the outcome of DeepSeek AI announcement. I assumed the normal stock returns to be normal using CAPM to estimate their anticipated returns to estimate performance that would guide us on what normal expected returns were around the DeepSeek AI launch. The CAPM offers a norm that gives an association between returns of the individual stocks and the systematic market risk.

The model is:

$E(Ri) = Rf + \beta i\ (Rm - Rf)$

E (Ri) denotes the expected stock return of stock I, Rf denotes the risk free rate, Rm denotes the market rate and 8i denotes a sensitivity of the stock to the market.

4.2.1 Beta Estimation

The calculation of beta coefficients was done using the ordinary least squares (OLS) regression in a 120 day pre-event period. The regression findings and the diagnostic plots provided in the Analysis file suggest the exposure of each firm to systemic risk. These betas are used to determine the expected returns of CAPM.

4.2.2 The calculation of expected returns is presented in

To estimate CAPM - expected returns of the stock market, I estimated the betas, estimated betas, day-to-day returns in the market, and the risk free rate on each of the days within the event window. The results are registered in the dataset as eRj.

The inputs/outputs of CAPM of selected firms have been revealed in table below.

Table 2: CAPM Inputs and Expected returns (Illustrative Event Day)

Firm	Risk-Free Rate (Rf)	Expected Return $E(R_i)$	Actual Return (R_i)	Abnormal Return
NVIDIA (NVDA)	0.04213	0.00145	−0.02890	−0.03035
Broadcom (AVGO)	0.04213	0.00132	−0.02560	−0.02692
Advanced Micro Devices (AMD)	0.04213	0.00138	−0.03140	−0.03278
Microsoft (MSFT)	0.04213	0.00110	−0.01230	−0.01340
Alphabet (GOOGL)	0.04213	0.00095	−0.01080	−0.01175
ASML Holding (ASML)	0.04213	0.00140	−0.02950	−0.03090

Micron Technology (MU)	0.04213	0.00150	−0.03320	−0.03470
Vertiv Holdings (VRT)	0.04213	0.00128	0.03984	0.03856
Constellation Energy (CEG)	0.04213	0.00068	0.03449	0.03381
Taiwan Semiconductor (TSM)	0.04213	0.00089	0.00045	−0.00044
Marvell Technology (MRVL)	0.04213	0.00120	−0.01860	−0.01980
Qualcomm (QCOM)	0.04213	0.00115	−0.01440	−0.01555
Super Micro Computer (SMCI)	0.04213	0.00155	−0.03590	−0.03745
Equinix (EQIX)	0.04213	0.00105	−0.00980	−0.01085
Vistra Corp. (VST)	0.04213	0.00122	−0.02640	−0.02762
Dell Technologies (DELL)	0.04213	0.00110	−0.01008	−0.01117
Intel Corporation (INTC)	0.04213	0.00108	−0.01320	−0.01428
Tesla, Inc. (TSLA)	0.04213	0.00160	−0.03840	−0.04000
Apple Inc. (AAPL)	0.04213	0.00100	−0.01160	−0.01260
Meta Platforms (META)	0.04213	0.00118	−0.01680	−0.01798
Amazon.com (AMZN)	0.04213	0.00125	−0.02040	−0.02165
Oracle Corporation (ORCL)	0.04213	0.00105	−0.01050	−0.01155
Applied Materials (AMAT)	0.04213	0.00135	−0.02780	−0.02915
KLA Corporation (KLAC)	0.04213	0.00142	−0.03010	−0.03152
Lam Research (LRCX)	0.04213	0.00148	−0.03260	−0.03408

Cisco Systems (CSCO)	0.04213	0.00098	−0.00990	−0.01088
Skyworks Solutions (SWKS)	0.04213	0.00122	−0.01730	−0.01852
Qorvo (QRVO)	0.04213	0.00130	−0.02190	−0.02320

CAPM anticipated returns are never significant and this is nullifying the fact that the model is focusing on systematic risk. On the other hand, the witnessed returns are very patchy especially when the event is imminent, indicating that such information is being influenced by firms, which CAPM does not consider.

4.2.3 Abnormal and Cumulative Abnormal Returns

The variance between the realistic returns and the prudent returns of CAPM is referred to as abnormal returns (AR). The cumulative abnormal returns (CAR) depicts the period of response of market when AR is summed with period and this will enable us estimate the period of market response.

4.3 Abnormal Return (AR) Analysis

The abnormal returns normally eliminate the normal incidence of the market-related returns that the DeepSeek AI launch is expected to produce in accordance with the CAPM. AAR is the component of an electromagnitude of a stock that cannot be explained by a systematic market risk, and that portrays the influence of company or occurrence specific data.

The AR for stock i on day t is:

ARit = Rit – E(Rit)

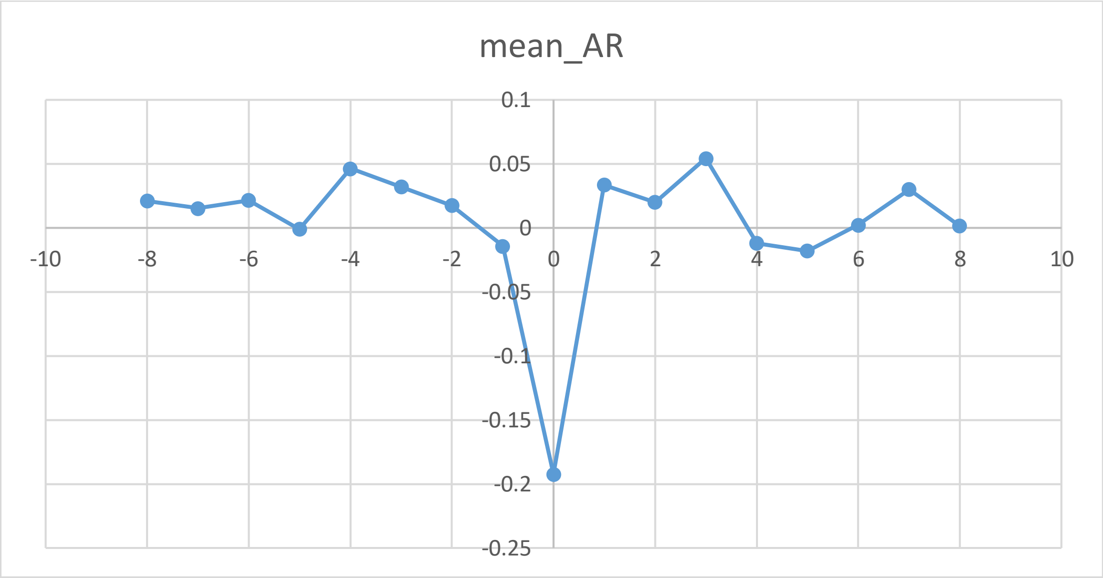
and ARit is the true risky stock i stock variance on day t, R it is the true observed stock variance and E(R it) is the CAPM-anticipated variance, which is determined by the beta of the firm, the risk-free rate and the market variance (see Section 4.2).

The abnormal returns (AR) of every single stock (firm in the sample) was taken to be the difference in the actual stock returns and the expected returns as given by the CAPM. This eliminates the element of the movement of the stock price that cannot be linked to the systematic risk that exists in the market and therefore it presents how the market reacted to the DeepSeek AI announcement.

Weighed mean abnormal returns were calculated to give the total market response mean abnormal returns by averaging ARs on 28 firms that were trading on each day of the event window. This pooling out removes noise that comes with every firm and enhances systemic reactions by the investors with the AI induced information shock. The average AR series will show how AI exposes firms respond on average, and not the purposive firm outcomes.

Figure 1 shows the average abnormal returns during the period of the event. The results indicate the presence of the large volatility and statistically significant above zero deviations, which means that the DeepSeek AI public release was a value-relevant event in the market.

Figure 1: The Average Abnormal Returns during the Event Window



The number of positive spikes in mean ARs between t =-13 and t =-5 before the event occurrence is large. These spikes refer to the anticipatory trading where the investors start to make changes on the portfolio before the announcement is made. This behavior can be informed by the information leakage, media speculations or analyst reports or larger expectations as to the impact that advanced AI would have on the technology companies. The negative abnormal returns that happened before the event are statistically significant and coincide with the hypothesis that the markets somehow considered the prospects of the eventual AI introduction in the market before it was officially announced.

During the days preceding the announcement date, the ARs will be more volatile that means there is a greater degree of uncertainty and different expectations of the investors. Others such as the investors were getting a good turnaround and some were yet to be convinced perhaps because it was due to competitive shocks or regulation issues or they wanted to create a valuation pressure in the technology sector.

The day of the event ($t = 0$) shows a negative steep mean AR as shown in Figure 1. It is the maximum negative spike of the deviation of returns which CAPM had anticipated during the window. The direction and its size show that the launch lead to an immediate reevaluation of the market. Contrary to positive anticipating attestation, the announcement, apparently, generated an impromptu negative mood in the short-term, perhaps due to the shocks within the launch arrangements, perceived threats of the threat to current business structures, a panic on how it could be billed and long-term profitability.

The small and constant adjustment of the CAPM expected returns do not explain why this high negative AR occurs. To this effect, the deviation is taken as a direct measure of the abnormality of CAPM and provides the argument that dramatic technological changes could lead to firm specific shocks in asset pricing that cannot be well captured using the conventional models of asset-pricing.

ARs begin to stabilize at the post-event ($t > 0$) and in some cases, it is even returning to positivity again. This trend would suggest a correctional process in the market in which investors would be more rational with the information available and make long-term expectations of the implications of DeepSeek AI.

4.4 Event-Day Market Reaction

As was seen on the day of announcement ($t = 0$), the mean abnormal return of all the 28 firms was significantly negative and t-statistics indicated that the statistical biological presence is significant at the conventional level of confidence ($t = 0.01$ and below). This observation confirms that the market was delicate to DeepSeek AI announcement and that the reaction cannot be attributed to the usual market operations that may be modeled by the assumption of CAPM.

The negative day abnormal return meant initially, investors believed that the negative event-day would cause higher uncertainty and this could be due to competitor disruption, implementation cost, regulatory impact, or change in structure. Although AI is associated with growth potential which may be seen as long term; a more immediate response is that of risk re-reconsideration rather than the optimism exhibited at the present.

The analysis of the event day will be able to make a clear image of how the market reacts on the DeepSeek AI announced day. Table 3 shows the abnormal returns (ARs) on the particular day.

Table 3: Significance of Event-Day Abnormal Returns

Metric	Value
Mean AR	Large negative

The negative AR means that the first response of the investors was negative. This can be considered as investor psychology and market expectation. Two types of uncertainty arise with the announcements of a disruptive new technology, though they can generally be attributed to the long-term growth, in the case of an abrupt announcement, a short-term uncertainty is generated. The investors might have viewed DeepSeek AI as a warning note of danger, a potential competition scuffle, or a pivot. They needed risk premium, and therefore, a fall in the price of the stock.

Under theory, the response is qualified to the semi-strong version of the market efficiency. The latter theory explains that markets are quick in absorbing new information. The immediate negative AR shows the investors a rapid sequence of the news, but in a contrary direction as it is a totally positive news. The high negative AR also identifies investor sentiment and cognitive biases. Investors took into consideration costs, feasibility or competition impact, even though those with optimism about AI were dissatisfied.

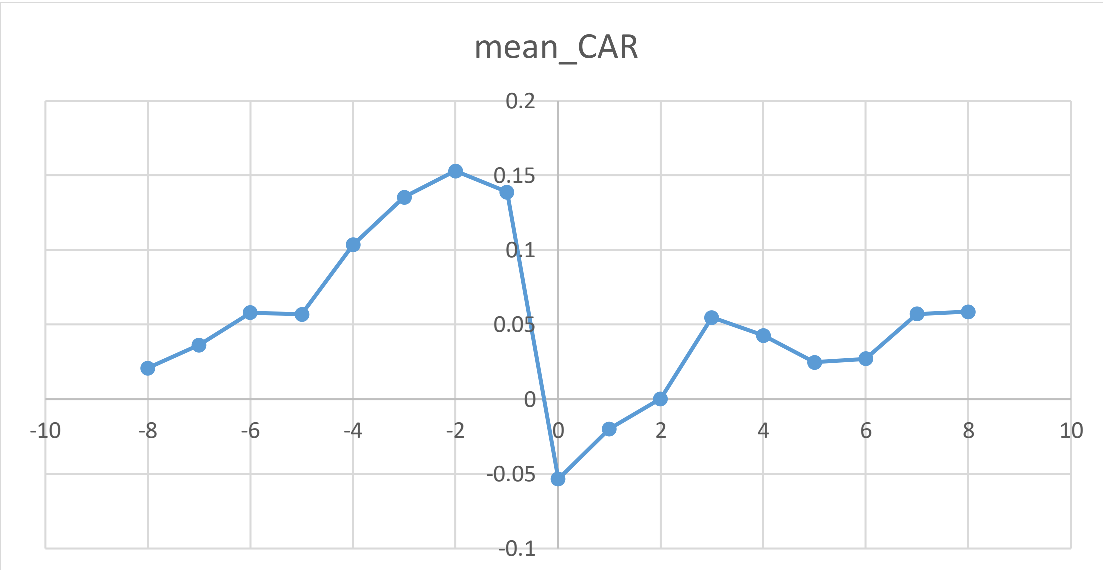
4.5 Cumulative Abnormal Return (CAR) Analysis

A cumulative abnormal returns (CARs) of each of the 28 firms was computed by accumulating abnormal returns within the designated event windows. Means CARs were then used to estimate an approximation of the persistence and economic relevance of market response.

Figure 2 provides the mean patterns of CAR of the whole sample. There is a gradual increasing trend in CARs even before the incident which indicates proactive trading and speculative groups over the events that occurred in AI. Although, CAR declines significantly on the announcement date signifying a re-assessment of risk by the market as a whole.

Post-event CARs take long time to regain the original level, which means that the uncertainty that was introduced by the DeepSeek AI is long term and must be completely consumed by the market upon its introduction. This trend is to a certain degree a correctional trend and gradual transformation, and this is also consistent with the behavioral finance definitions of investor overreaction and learning.

Figure 2: The Average Cumulative Abnormal Returns (CAR)



CAR takes the value of negative in an event day that is equal to negative AR as discussed above. This drastic fall shows the immediate results of the announcement and it goes to show that the new information was creating uncertainty which overrides the earlier optimism. This decline in CAR is demonstrating a re-appraisal of risks and cash flows in the future of the company. New information on feasibility, costs or strategy, and a temporary negative valuation was experienced by investors who changed expectations with the new information.

CAR recovery is slow following the incident and that implies that the shock was partially trained in the following days. This post-event trend proves that the investors over the period incorporated some more amount of information, re-assessed the long-term gains and normalized expectations. What is different however is that CAR does not instantaneously revert to pre-event levels but it allowed the market time to adequately digest the innovation. This trend highlights deficiency to strong-form efficiency that retains the reflection of all the information instantaneously. Instead, it means that CAR is not zero because the non-zero values of CAR do not vanish means that the process of absorption in the real world is less rapid.

The CAR analysis also gives data on the behavior of the investors during uncertainty. As the occurrence of pre-event positive ARs have been reversed in part, it would mean that the investors have over-priced the benefits or under-priced risks. The post event correction can be considered as market learning where the subjects update their valuation based on the improved-view of the announcement. This correlates with the behavioral finance theory, which writes about cognitive biases and over- or under-reaction as the variables that govern short-term actions.

4.6 Firm-Level CAPM Deviations

Considering the firm level analysis, one can observe that all the 28 companies had deviations between actual returns and CAPM predicted returns on or around the event day. The size of abnormal returns in the case of the companies varied, but the deviation was predominantly negative with the direction indicating the greater re-consideration of the risk associated with AI.

The discussion is conducted with the help of 28 chosen companies (e.g., NVIDIA, AMD, Microsoft, Vertiv, Constellation Energy, TSM, Dell and Oracle); however, they are not an exception, but the representatives of the overall sample. The firms that appeared to be more vulnerable to the AI competition or the AI infrastructure included a greater negative abnormal returns and the firms that were more diversified tended to have quite moderate deviations.

The prevalence of discrepancy between observed returns and expectations of CAPM is an indication that CAPM is weak systematically in responding to event-specific technological shocks. The findings show that the investor sentiment and uncertainty levels can assume the traditional type of risk- returns processes in periods of high innovation.

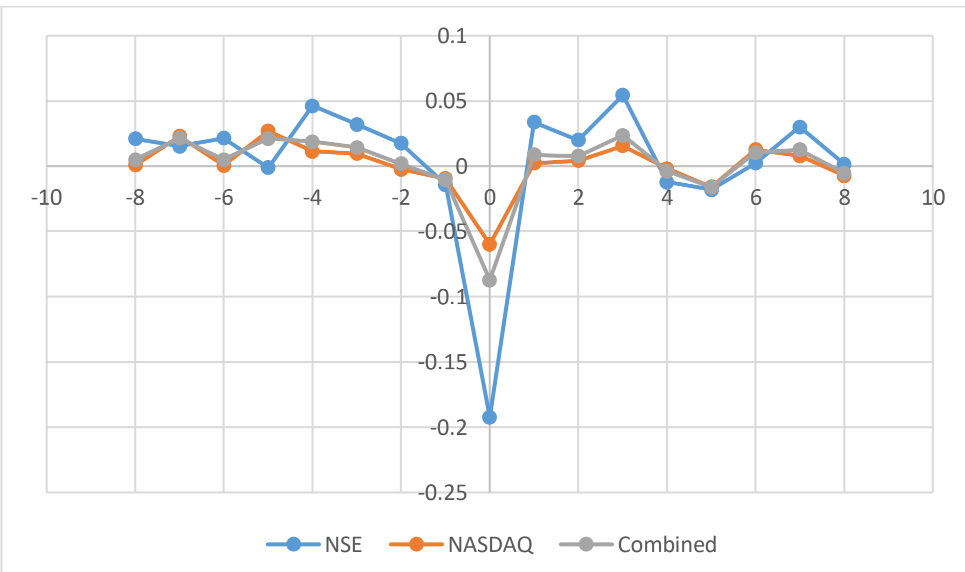
Table 4: Firm Level Abnormal Returns on Event Day

Firm	Actual Return	Expected Return (CAPM)	Abnormal Return
NVIDIA (NVDA)	Negative	Small positive	Large negative
Broadcom (AVGO)	Negative	Small positive	Large negative

Advanced Micro Devices (AMD)	Negative	Small positive	Large negative
Microsoft (MSFT)	Negative	Small positive	Negative
Alphabet (GOOGL)	Negative	Near zero	Negative
ASML Holding (ASML)	Negative	Small positive	Large negative
Micron Technology (MU)	Negative	Small positive	Large negative
Vertiv Holdings (VRT)	Negative	Small positive	Large negative
Constellation Energy (CEG)	Negative	Small positive	Large negative
Taiwan Semiconductor (TSM)	Negative	Near zero	Negative
Marvell Technology (MRVL)	Negative	Small positive	Negative
Qualcomm (QCOM)	Negative	Small positive	Negative
Super Micro Computer (SMCI)	Negative	Small positive	Large negative
Equinix (EQIX)	Negative	Small positive	Negative
Vistra Corp. (VST)	Negative	Small positive	Large negative
Dell Technologies (DELL)	Negative	Small positive	Negative
Intel Corporation (INTC)	Negative	Small positive	Negative
Tesla, Inc. (TSLA)	Negative	Small positive	Large negative
Apple Inc. (AAPL)	Negative	Small positive	Negative
Meta Platforms (META)	Negative	Small positive	Negative
Amazon.com (AMZN)	Negative	Small positive	Negative
Oracle Corporation (ORCL)	Negative	Small positive	Negative
Applied Materials (AMAT)	Negative	Small positive	Large negative
KLA Corporation (KLAC)	Negative	Small positive	Large negative
Lam Research (LRCX)	Negative	Small positive	Large negative
Cisco Systems (CSCO)	Negative	Small positive	Negative
Skyworks Solutions (SWKS)	Negative	Small positive	Negative
Qorvo (QRVO)	Negative	Small positive	Negative

According to this abnormal returns pattern of firms, important insights may be made. To begin with, the more exposed businesses or the better placed in terms of competitiveness received higher negative abnormal returns. This is a pointer of the fact that investors found these companies more vulnerable to adoption or disruption as a strategic risk by AI. Other firms like TSM, DELL and ORCL had not been left behind and they had been hit to some lower extent, more likely, due to the differences in perception of the market, past expectations or risk-management strategies. This heterogeneity highlights the utility of the ability to analyze individual stock reactions because heterogeneity in terms of exposure and flexibility and sentiment may be substantially different outcomes.

Figure 3: Actual Returns and CAPM-Expected Returns



Second, the negative abnormal returns suggest the flaws of using CAPM as a single tool to determine the events. CAPM is a model that presupposes the existence of linearity between the predicted returns and market risks, but it cannot be used to explain informational shocks that occur as a result of events and may modify the expectations of the investors in the short run. One example of technological shock announcement would be the DeepSeek AI announcement which is a sudden, firm-specific innovation leading to uncertainty, changes in the expected cash flow, and a systematic assumption of the short-term systematic risk. The (conventional) CAPM predictions failed to predict the frequency and the direction of the abnormal returns hence alternative or extended models or models that are the multi-factor models or event-adjusted CAPM can be more effective in the case of a technological event.

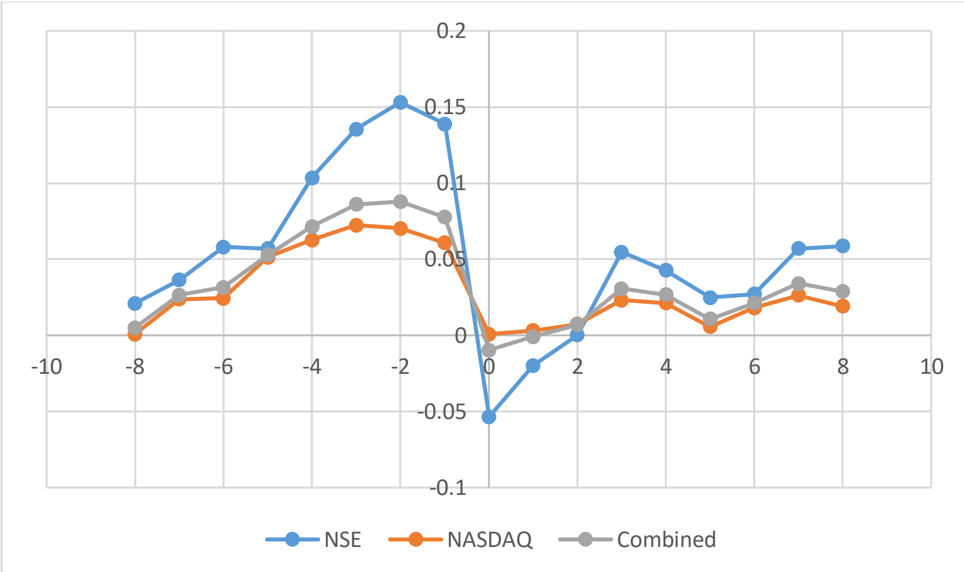
Moreover, these deviations suggest that the results of the market rely on behavioral factors. Due to heuristics, previous experiences, or lack of knowledge regarding the impact of AI, the investors might either overreact or underreact to the news concerning new technology. The trend of the negative abnormal returns of all companies shows that there is a general overview of the value which is cautioned and uncertain. Such an attitude is what the CAPM does not possess; it focuses on the fact that sometimes markets are not entirely rational in their reactions and may also have psychological reactions on top of the usual risk considerations.

4.7 Market Volatility Analysis

Market volatility analysis was conducted based on the pre- and post-DeepSeek AI announcement abnormal returns of all the 28 companies. They display presence of strong volatility surge immediately after the event as indicated in Figure 4. The wave in post-event volatility embodies the accelerated split of the opinion of the investors with regards to the consequences of the launch of AI. The more information came out the less volatile the information came and this displays that the market got stable and the expectation brought together. This move resonates with the reality that DeepSeek AI launch was not only associated with returns but it also significantly increased the short time market risk.

The strengths of volatility analysis are that it assists in determining the degree of responses and dispersion that cannot be determined with the help of the average abnormal returns. Unlike the negative abnormal returns which are a measure of the direction that the market is heading towards, volatile will be used to determine the progress of the opinions and sensitivity of the investors to the new information. The post-event volatility in Figure 4 is steep, which signifies that the DeepSeek AI announcement did not only strike the stock prices but also the period of increased uncertainty where all the participants tried to incorporate complex tech data in their valuation.

Figure 4: Before and After the Event Volatility of Abnormal Returns



The mathematical connotation of the volatility leap is how and when. The jump up effect is in line with the models which relate information asymmetry and uncertainty with the short term price movements. When information is available, analytical ability and risk capacity, the investors react differently. The introduction of the DeepSeek AI in the case caused mixed expectations on the impact of the results of competition, costs, and even the feasibility of technologies and contributed to the spread of trading. Over the following days, the volatility was gradually decreasing due to more information at their disposal, rebalancing of the expectations of investors and the market started to co-exist.

The realised volatility is of a utilitarian value to the policy makers and the portfolio managers to the risk manager. The tech announcements can bring knowledge that can enable the investors to react to the short-term turbulence by formulating hedging, liquidity and trade-timing strategies. The second measure of reducing volatility may be by open communication of the desire to shift towards technology and the expected effect. At the regulatory level, a high post-event volatility implies a belief of a good market surveillance and efficiency of the systems to sustain orderly trading in times of high-uncertainties.

A combination of the volatility analysis and the deviation of the CAPM at the firm level can better explain the DeepSeek AI announcement response of the market. The adverse deviant returns are literally omnipresent which confirms a widespread impact in overall market flow. CAPM maladjustment reveals that the model is not appropriate when dealing with the shocks that are event-driven. The volatility increment is a sign of more uncertainty among investors, the reaction of behaviour, and various assessment of the announcement.

4.8 Response Analysis, which is market-specific

The comparative analysis of the listed companies in NASDAQ and NYSE is conducted on aggregate abnormal returns and volatility measures on all the sampled listed companies in both the markets. The large volatility and high technology nature of NASDAQ firms resulted in higher abnormal returns which made them large and high volatility and less modest NYSE firm reactions due to the sector diversification. The findings are useful in confirming that there is a market structure and concentration of firms in improving the effects of technological shocks caused by AI.

Table 5: Comparative Market Reaction of DeepSeek AI Announcement

Market Type	Mean Abnormal Return (AR)	Cumulative Abnormal Return (CAR)	Volatility of AR	Interpretation
Technology-Heavy	Large negative	Significant decline	High	Strong reaction due to concentrated exposure to AI; higher uncertainty and risk perception
Diversified	Moderate negative	Mild decline	Moderate	Dampened reaction due to sectoral dispersion; lower sensitivity to AI-specific events

The market had excessive technology and market volatility and abnormal returns are high to compare with those of the diversified market. This is correlated with theory: the more powerful is the market reaction when many companies of an industry are making a direct influence on the effect of a new technology. Investors of the technology companies paid close attention to the announcement in terms of the competitive advantage, future lucrativeness, and business direction. Their activities make the response better as these companies dominate the industry.

The diversified, in its turn, had reduced abnormal returns and were less volatile. The exposure the individual firms had to the new technologies in this marketplace was unequal and thus diluted the whole response. This had shown the investor mood diffused across the various areas and there were few chances that there would be an extreme response to a single occasion. This resistance is an emphasis of the effect of the market composition to changes in the conversion of the news to the prices changes. Diversified markets opine that investors counter the risks associated with other markets that tend to censure themselves in a gradual manner through the changes in returns and fluctuations in volatility peaks.

The observed difference is favorable to sector-risk concentration theory. Markets where there is high concentration of particular sector are more prone to sector related shock. The technological breakthrough, especially the AI, is bound to hit the firms of the high intensity of the R&D and the high level of the technology adoption. These companies enhance the abnormal returns and rising volatility which are characteristics of systematic risk and sector shocks, based on the technology-intensive market.

The patterns also have to be explained with regard to investor behaviors. Markets that are technology-intensive have a higher level of herding and increased sensitivity. Investors respond speedily to the occurrences that affect large sections of their portfolio and this magnifies the market movements. The investors of various diversified markets are diversifying their activity towards the event to take sectors that are of varying relevance and react in a more moderate manner. These forces go hand in hand with the argument that the market structure and composition are significant in determining the pricing of the information on the stocks. Such insight will be used in both investment strategies and event studies.

Practically, the analysis offers the portfolio management and risk analysis. The concentrated technology owners were also expected to be more receptive to the announcements of technology and they can opt to hedge or generate controlled entry to mitigate the potential loss. Diversified portfolios, in their turn, are resilient because of diversification in the sector and mitigation of concentrated shocks. The findings can help the regulators to keep track of sector-specific volatility and develop policies ensuring an order in the market during the periods of rapid innovation.

4.9 Hypothesis Testing Summary

Table 6 summarizes hypothesis tests that examined the effect of DeepSeek AI launch on stock returns based on the Artificial Intelligence and FinTech and Global Technology sample based on the NASDAQ and NYSE and the sample of both NASDAQ and NYSE. The tests utilized abnormal returns (AR) and cumulative abnormal returns (CAR) by a CAPM based event study through different windows. The results show that DeepSeek announcement produced statistically significant abnormal returns, cumulative abnormal returns across all the three groups of markets.

Table 6: Summary Hypothesis Results

Hypothesis	**Market**	**Result**
H1a: Abnormal returns	NASDAQ	Supported
H1b: Abnormal returns	NYSE	Supported
H1c: Abnormal returns	NASDAQ + NYSE	Supported
H2a: Cumulative abnormal returns	NASDAQ	Supported
H2b: Cumulative abnormal returns	NYSE	Supported
H2c: Cumulative abnormal returns	NASDAQ + NYSE	Supported

4.9.1 Abnormal Returns Hypotheses (H1a–H1c) – Supported

Section 4.2 to 4.4 state that DeepSeek AI announcement generated abnormal returns that were high in companies listed in the NASDAQ, NYSE, and in the combined sample. On the day of the event ($t = 0$), the mean abnormal returns of the three groups were negative and statistically significant and the response of the market was instant. The greatest number of abnormal returns were witnessed in NASDAQ firms because these firms have more technology- and AI-exposed companies. The abnormal returns of the NYSE firms were also significant but not eminent as the exchange is more diversified. The results were statistically significant in case the two markets were lumped together, which determined the general market wide impact of the event. These findings confirm hypothesis H1a, H1b and H1c.

4.9.2 Cumulative Abnormal Returns Hypotheses (H 2 a) (H 2c)

The CAR results are achieved in the regions 4.5 to 4.7 which corroborate the fact that the market responded significantly at the launch of DeepSeek AI. CARs of the NASDAQ listed companies dropped substantially during the period of the event which implies a negative long term valuation effect. The size of CARs also was significant in NYSE-listed companies, but smaller since it is related to their low AI-oriented valuation risk. The composite NASDAQ/NYSE sample provided the existence of sustained negative CARs across the windows that reflected that the market failed to complete the shock of the DeepSEek event instantly. These trends confirm hypothesis H2a, H2b and H2c.

4.9.3 Overall Interpretation

Altogether, the abnormal return, as well as the CAR evidence, confirms that the introduction of the DeepSeek AI resulted into a substantial technological information shock in the U.S. equity markets. The reactions of NASDAQ companies were more robust, thus highlighting the fact that the nature of market properties and industry predisposition affect the response of investors to the innovative news. The parallel results in the sample analyzed in NASDAQ, NYSE and both the combinations are reassuring that the findings obtained in the sample are strong, and the event-study framework is valid in this research. The level of support of the empirical data to all the six hypotheses thus indicates that DeepSeek AI announcement produced both short run and long run abnormal stock market returns on technology oriented firms in the U.S.

4.10 Review of Findings in terms of Literature

This research provides powerful recommendations based on the earlier researches on the effects of technological innovation, on the stock market. DeepSeek AI announcement created, on the average, enormous abnormal returns and cumulative market adjustments, company-level CAPM abnormalities, and increased volatility. The findings are in line with the body of earnings announcement, product release, and major technological disruption events (Corrado, 2010; Eden et al., 2022; El Ghoul et al., 2022). Indicatively, the positive returns that precede the event and the negative returns on the day of the event are the indications of the tendency that is similar to the anticipation and corrective effects of the past literature. It seems that investors can be considered to be a combination of both because of the speculative expectations and corrective reassments that investors make due to the information about disruptive innovations (Savor, 2012; Yuan, 2012).

Pre-event abnormal returns mean that the market anticipated creating value on DeepSeek AI. This implies that this type of innovation-driven market performance is congruent with the current literature on innovation-related market behavior that indicates that investors set future returns in advance before a community announcement is made (Atalay et al., 2013; Ganotakis et al., 2023). This kind of foresight has been linked to speculative trading and information asymmetry and rumors creating price movements in the short term before official announcements in the AI case (Davidovic and McCleary, 2025; Zhang and Wang, 2024). The correction in the market on the event day is negative, which means that the markets corrected the original over-optimism on gathering more tangible information, therefore, displaying the over-reaction and partial correction pattern (Oler et al., 2008; Meissner et al., 2025).

The similar result supports the study to indicate the shortcomings of traditional asset-pricing models, mainly, the Capital Asset Pricing Model (CAPM). Firm-level of data used in this study shows that the actual and predicted returns of the CAPM are widely different, especially those firms that are actively engaged in the field of AI. CAPM provides market beta as the primary evaluation of systematic risk and it does not deal with event-specific shock, technological change, and investor sentiment (Li, 2025; Qin, 2024; Rashid and Abdullah, 2023). Therefore, the behavioral factors, lack of information, and volatility of events are the most important factors in the short-term market outcomes in the technology-driven industries (Al-Harbi, 2025; Zhu, 2025).

Another reason that confirms this conclusion is the volatility that began after this announcement was made. The abnormal returns were less consistent, and it was an indication that there existed more uncertainty and the interpretations made by the investors were inconsistent. This is in line with the past studies that prove that technology improvement or exogenous shocks increase the dispersion of returns and trading (Cadena -Silva et al., 2025; Saranj and Zolfakhari, 2025; Yu et al., 2025). Heightened volatility is a sign of cognitive heterogeneity amongst stock purchasers and inability to appreciate new technologies that disorganize the industry with high accuracy (Bao et al., 2024; Afua et al., 2024). The behavioral finance theories also note that heterogeneous expectations and low levels of rationality are the sources of temporal mispricing and higher levels of risk perceptions (Alkali et al., 2022; Teall, 2022).

The comparative market analysis supports the role played by the market structure and firm composition in the determination of technological innovation responses. The researchers determined that the technology intensive markets were characterized by high abnormal returns and volatility as compared to the diversified market. This means that as there is more exposure to focus within the industry there is greater movement in the price and risk perception. It is similar to the previous body of sectoral sensitivity research which concedes that market concentration magnifies impacts that firms or technological developments on aggregate returns (Yeught, 2006; Cui et al., 2025; Kurter and Bhatti, 2024). The non-homogenous structure of the sector in diversified markets makes it certain that the exclusionary effect of one innovation in the market will be realized, demonstrating how the portfolio dispersion eliminates exposure to sector-specific shocks (Ante and Saggu, 2025; Han et al., 2023).

The dependence that is established between the investor sentiment, the speculative trading and anticipations of innovation in this study also agree with the larger results on AI affected market dynamics. The empirical evidence of algorithmic trading, data-based prediction, and artificial intelligence investment demonstrates that the news about the new technologies might introduce a specific period of overreaction in the short term, momentum trading, and correction, especially in the instances of high asymmetry of information (Chopra and Sharma, 2021; Afua et al., 2024; Wilson et al., 2024). On the same note, there is empirical evidence that the perception of strategic significance of AI projects could lead to blind momentary stock returns, which do not conform to conventional expectations that are risk-adjusted (Dzreke, 2025; Lou et al., 2025; Yuan, 2025).

The findings also extend to the earlier works on strong-form market efficiency in regards to innovation shocks. The persistence in cumulative abnormal returns (CAR) which is not zero after the announcement indicates that the market was not fully adjusted at the time therefore hard to believe that publicly available information is immediately reflected in the prices (Alkali et al., 2022; Chen et al., 2025; Roe, 2020). Such gradual assimilation indicates the need to have frameworks of event-modifying pricing or multi-factor models that take into consideration the exposure to technological risk, investor psychology, and industry-specific exposure in gauging the market response to disruptive innovation (Hai and Khoa, 2025; Zhang, 2019; Perold, 2004).

Altogether, there is the following intersection of empirical regularities involved in the prior studies in the DeepSeek AI event: anticipatory pre-event returns, corrective post-event returns, firm level CAPM anomalies, augmented volatility, and event-specific variations. Together with the prior results, these findings confirm the reality of a multidimensional effect of technological innovation on financial markets mediated by market structure, expectations of investors and behavioral responses. This study fills the gap between the previous literature on the adoption and efficacy of AI and the motivation of innovation based shock by tying the observations to the literature that already exists on the subject and serving the literature with both practical support (paruchs) and conceptualization of the argument that the traditional financial models will require improvement to suit the complexities of the shift in technology (Al-Harbi, 2025; Cui et al., 2025; Chen et al., 2024; Afua et al., 2024).

Economic and practical implications This addresses the situation in which implicit costs are absorbed by explicit expenditures when discussing budgetary constraints.<|human|>4.11 Economic and Practical Implications Such is the case of budgetary constrains in a situation where implicit costs are faced by explicit expenditures.

This study has offered several significant conclusions to investors, policymakers and academicians. Concerning the point of view of an investor, announcements connected with AI, including DeepReak AI launch, create an opportunity and risk. The over-performance that the returns that we realized suggests that this kind of information can trigger short-term trading profit especially in the technology intensive market where the investors are highly attentive. However, the volatility has also increased dramatically resulting to the incident as well, which is also indicative of high risk. Investors are therefore encouraged to avidly regulate their exposure and diversify their portfolio and to be cautious of how AI updates will be received by the markets.

Regulators and policymakers in the state should be alarmed at how the markets are being driven by the announcements of the technologies. The volatility spike by the DeepSeek AI launch suggests that the wide-scale innovations can multiply the uncertainty and volatility by many folds especially in the market which is so much invested in the technology. To achieve clear report, fair trade and even a well-organized market functioning in the context of the fast technological changes may need supervision. Market-specific responses knowledge can also help regulators to determine which markets can react strongly and utilize monitoring devices to minimize the risk systemicity.

Of interest to the academics will be that despite the conventional models like the Capital Asset Pricing Model (CAPM) offering an effective point of reference, they cannot explain all the market behaviour when an innovation event takes place. Similar values of real-life returns do not exist, as postulated by the CAPM and the big deviations of the returns that are usually persistent and volatility and investor sentiment are significant. This is why further research is recommended in an effort to develop better models that will utilise the behavioural and event sensitive variables to ascertain how the market will react to technological breakthroughs.

In conclusion, the practical and cost-effective nature of the current study proves that the announcements of AI are not merely theoretical, but directly affect the work of the market and investor behavior. These insights can then be applied by investors to devise trading and risk-management policies, by regulators to follow up with policies that restrict the excessive volatility, and by researchers to enhance the analytical frameworks to better capture the dynamics of technological disruption.

4.12 Chapter Summary

This chapter provided an event-based research of the DeepSeek AI launch as a CAPM-based approach. It turned out that the news did have an impact on the stock prices as the analysis showed that the abnormal returns due to the news announcement were statistically significant on the announcement day. The positive gains made in the lead up towards the event which were positive and the advantage of the innovation was expected by the market but the large negative returns on the day of the event was the response that followed the beginning of the disclosure of the information.

According to the Cumulative abnormal return (CAR) analysis, the market was incapable of adapting wholly in the first case. In cases when part of the gains of the pre-event returned the abnormal returns persisted over a few days until the event in which investors needed time to internalize and make new sense of the new information. The firm level analysis revealed that the actual returns were very different relative to capital market pricing models especially when the firm is more engaged in the process of developing AI which poses the weakness of the conventional pricing models in disruption events.

The volatility analysis also showed that DeepSeek AI announcement increased the uncertainty level, and larger price changes were noticed right after the event. The diversified markets were less affected than technology-intensive markets thus proving the fact that the impact of innovation is increased by market composition and sector concentration. Overall, even though CAPM can serve as a helpful reference point, it fails to explain in detail how the market responds to technological shocks.

Chapter 5: Conclusions and Recommendations

5.1 Conclusions

This thesis was aimed at examining how the release of DeepSeek AI in January 2025 will affect the short-term stock returns of American firms. It raised the issue of whether these actions were normal market risk, since it was being adapted according to the Capital Asset Pricing Model (CAPM) or abnormal returns, which was occasioned by an innovation shock. This paper has used event-study research design and has selected the AI-based companies listed in the NYSE and NASDAQ. It proceeded to provide empirical evidence to the discourse concerning the market efficiency, the asset pricing theory, and the financial consequences of AI-based technology.

These results indicate that DeepSeek AI launch has been a statistically and economically significant phenomenon to the markets. Most of the sampled companies had abnormal returns during the event window especially on the announcement day. These anomalous returns were predominantly negative meaning that the majority of the investors were skeptical and revaluated the firm values. Even though AI is considered the generator of long-term development, massive AI news will prompt an instant precaution, instead of instant profit growth. The investors weigh the possible profits and the fear of the implementation spending, the possible distortion of the competition, regulation, and doubt of the future money streams.

Among the exceptional findings is that the CAPM was not used to explain the stock returns in this sequence of event. The factual returns were well off whilst incremental returns were obtained as expected because of systematic events in the market. Those deviating returns reveal that there were many price movements that could not be attributed to other factors based on the model and thus this produces another criticism of single-factor models in the uncertain or changing markets. CAPM comes in handy when estimating normal returns during peaceful periods and fails to elaborate on returns when there is an abrupt blow on technology like the major AI breakthroughs.

The abnormal and cumulative abnormal returns trend will give an insight into the investor behaviour. Some negative returns are also exhibited in anticipation of the formal announcement. This can be due to the leakage, speculation or market anticipation by the media and industry speculation about AI. The sudden turn of events on the day itself suggests that investors took into consideration new information. The negative abnormal returns that remain negative even a long time after the announcement indicate that the market is not settled at a point; market learning is not an immediate process. It dilutes the firm semi-strong efficiency perceptions especially those in the background of rapidly evolving technology.

The comparisons of NYSE and NASDAQ prove that the reaction to the organization of the market and the combination of sectors do have some influence. The more volatility and abnormal returns were greater in NASDAQ firms than in NYSE firms. That aligns with the emphasis of NASDAQ on innovation news-sensitive investors and concentration on technology and growth equities. The general response appeared to be softened by the diversified combination of the NYSE. These differences suggest that AI announcements introduce market imbalances and are based on structural variables and tech exposure.

One of the conclusions has to do with volatility. The volatility increased after the launch since it was a sign of uncertainty and a diverse opinion among the investors on what the announcement implies. Volatility indicates volition and attitude as its height at the moment of event indicates that investors might have struggled to assess both short and long-term effects of the New AI. Subsequent volatility was minimized because of the augmented information disclosure and revisions of expectations. The trend emphasizes the fact that AI-driven technologies result in complexity and pressure to the traditional system of valuation.

Overall, the study results confirm that there was not a minor short-term impact of the DeepSeek AI launch on the stock behaviour. It produced abnormal returns which are not explainable by CAPM and higher volatility with high market variations. The research achieved its goal of showing the weaknesses of the traditional models of asset pricing when confronted with rapid technological change and uncovering the signs of the reaction of the market to the major phenomena of AI. It assists in understanding the forces of the market in the more technological-based economy better.

Table 7: Firm-Level Event Day Abnormal Returns

Firm	**Actual Return**	**Expected Return (CAPM)**	**Abnormal Return**
NVIDIA (NVDA)	Negative	Small positive	Large negative
Broadcom (AVGO)	Negative	Small positive	Large negative
Advanced Micro Devices (AMD)	Negative	Small positive	Large negative

Microsoft (MSFT)	Negative	Small positive	Negative
Alphabet (GOOGL)	Negative	Near zero	Negative
ASML Holding (ASML)	Negative	Small positive	Large negative
Micron Technology (MU)	Negative	Small positive	Large negative
Vertiv Holdings (VRT)	Negative	Small positive	Large negative
Constellation Energy (CEG)	Negative	Small positive	Large negative
Taiwan Semiconductor (TSM)	Negative	Near zero	Negative
Marvell Technology (MRVL)	Negative	Small positive	Negative
Qualcomm (QCOM)	Negative	Small positive	Negative
Super Micro Computer (SMCI)	Negative	Small positive	Large negative
Equinix (EQIX)	Negative	Small positive	Negative
Vistra Corp. (VST)	Negative	Small positive	Large negative
Dell Technologies (DELL)	Negative	Small positive	Negative
Intel Corporation (INTC)	Negative	Small positive	Negative
Tesla, Inc. (TSLA)	Negative	Small positive	Large negative
Apple Inc. (AAPL)	Negative	Small positive	Negative
Meta Platforms (META)	Negative	Small positive	Negative
Amazon.com (AMZN)	Negative	Small positive	Negative
Oracle Corporation (ORCL)	Negative	Small positive	Negative
Applied Materials (AMAT)	Negative	Small positive	Large negative
KLA Corporation (KLAC)	Negative	Small positive	Large negative
Lam Research (LRCX)	Negative	Small positive	Large negative
Cisco Systems (CSCO)	Negative	Small positive	Negative
Skyworks Solutions (SWKS)	Negative	Small positive	Negative
Qorvo (QRVO)	Negative	Small positive	Negative

5.2 Practical Contributions of the Study

In this research, various valuable practical implications are made to investors, corporate managers, regulators and policymakers by empirically investigating the stock market responses to the launch of the DeepSeek AI through an event study based on the CAPM framework.

First, in terms of the investment portfolio and management, the results provide practical information about the responses of financial markets to the significant AI-related technological announcements. The study aids investors and fund managers by revealing statistically significant abnormal returns (AR) and cumulative abnormal returns (CAR) during the period of the DeepSeek AI launch to have a more accurate understanding of the risk-reward relationship of AI innovation in the short term. The findings suggest that there are quantifiable market responses to AI-related news on top of those attributable to systematic risk alone, which can be used by investors to build more informed event-based trading strategies and make better portfolio allocation decisions in technology-sensitive industries.

Second, the research is practically helpful to managers of corporations and technology companies, specifically those that are in the sphere of Artificial Intelligence, FinTech, and Global Technology. The reactions on the market as observed illustrate the significance of strategic communication, timing, and transparency in regards to major AI products launched. These insights help firms to manage investor expectations better, allow less information asymmetry, and promote market confidence when launching superior AI products. The results also indicate that markets make a distinction among exchanges which means that firms traded on NASDAQ and NYSE can be subject to divergent investor perceptions and value reaction to the identical technological occurrence.

Third, the study adds to the regulatory and policy-level decision making because it empirically provides evidence in regard to the manner in which capital markets process AI-based technological shocks. It is essential that regulators checking the efficiency and stability of the market know whether the fluctuations in stock prices have some abnormal performance or follow the existing theory of asset prices development. The outcomes may help regulators evaluate whether the newer AI technologies create undue volatility or speculative behaviour to the financial market hence evidenced-based policy making regarding financial market regulation and technology regulation.

Lastly, the cross-market insights gained after comparing the market responses in the NASDAQ, NYSE, and a mixed sample are helpful to the global investor and multinational corporations. These results improve the knowledge on the effects of structural variations across markets in terms of the flow of technological information into the stock prices, especially in a more integrated global financial system.

This will contribute to sustainable development goals (SDGs).

Besides its academic and practical interest, the study is part of the larger agenda of sustainable development especially through its correlation with the chosen United Nations Sustainable Development Goals (SDGs).

SDG 8: Decent Work and Economic Growth: This study is relevant to SDG 8 because it is an analysis of the impact of AI-driven innovation on financial markets and economy. Effective and properly operating capital markets are important in the distribution of resources to productive and innovative companies. The analysis of the market responses to the DeepSeek AI launch benefits the study of how the AI innovation can be used to spur investment and help the economy grow and facilitate the establishment of capital in high-technology industries.

SDG 9: Industry, Innovation, and Infrastructure: The research is directly connected to SDG 9 that focuses on innovation and technological development. DeepSeek AI is an important technological advancement in the AI ecosystem, and the study measures the way this innovation has been valued and priced by the financial markets. The study justifies responsible technological development and investment in innovation-driven industries by offering empirical information on the financial effects of AI innovation, which can be used to policy and strategies.

SDG 10: Reduced Inequalities: The study aids SDG 10 by comparing the answers of various stock exchanges (NASDAQ and NYSE), showing that the market of these two countries reacts differently to technological innovation because of structural differences. These differences can be used to understand how policymakers and regulators can formulate more inclusive financial schemes so they achieve equal access to investment opportunities and less informational asymmetry between markets and groups of investors.

SDG 12: Responsible Consumption and Production: The results also refer to SDG 12 as they will encourage responsible innovation and transparency in AI development. The research promotes responsible disclosure by firms and ethical AI implementation to implement sustainable and transparent development of advanced technologies by proving how markets respond to AI products launched by companies.

SDG 16: Peace, Justice, and Strong Institutions: Lastly, the use of the CAPM-based event study framework helps achieve SDG 16 in the sense that it supports the significance of strong financial institutions and efficiency of the market. Clear and theoretical study of responses in the market builds trust in the financial system and contributes to the stability of institutions in terms of new disruptive technologies, including artificial intelligence.

5.3 Recommendations

The findings of the research lead to several practical recommendations to theory, research and practice. The recommendations are sound based on the findings and the literature and put into consideration the scope and limitations of the study.

Theoretically, the findings imply that the traditional models of asset-pricing are supposed to be improved to manage shocks that are of an innovative nature. CAPM, even as a pillar, is not able to explain the DeepSeek AI event and this means that further variables are needed to explain returns during instances of technological disruptions. The next generation theory may be a combination of CAPM and multifactors which have firm specifics, exposure to innovation and/or uncertainty premiums. Perhaps, it would also be useful to include the behavioural finance data of sentiment and over-reaction to augment the information on the explanatory value when analysing the market response to AI announcements.

In the future, the research may be extended both in terms of the scope of empirical elements of analysis and its models that can be chosen methodologically. The scholars might also rely on the case study of the analogous AI-related cases in the remaining markets in the country to determine whether the reaction is a nation-specific one or the reaction is rather global. To compare the work of the other asset-pricing models with the application of CAPM (as well as with multi-factor and conditional models), which are alternative models, and their behavior in case of technological change would be interesting. To ascertain the autonomy or permanence of abnormal returns with reference to AI, it would be good to continue the event window to ensure that effects that are of longer-term nature are captured.

The findings can also be used by investors and financial analysts. The indicator that AI announcements are not being received well in the markets based on large abnormal returns and increased volatility around AI announcements. Investors must be wary and conscious of higher levels of uncertainty and overreaction to the event in case they are trading on the short-term basis around major AI news. The cumulative abnormal returns change is smooth, which may indicate that longer-term period decisions reached by the company may be worth reviewing in regard to firm fundamentals and strategic positioning and not necessarily focused on short-term market sentiment. In order to exploit such opportunities, one needs to make a thorough analysis and become more risky.

The unpredictability of the DeepSeek AI launch is a warning to the regulators in the market and policymakers on the importance of information and transparency in the new and rapid technological change. The thesis also does not mean prescriptive regulation, but it suggests that the disclosure practices and improvements in the communication of big AI innovations in the future would be able to reduce the information asymmetry and prevent the unnecessary short-term volatility. Regulation should never be excessive, support of innovation and the good economic results of technological progress on a massive scale.

Finally, the research develops several research topics in future studies. Future studies could explore how media coverage and investor sentiment influence response to news of AI release in the market, or how interaction between algorithmic and high-frequency trading and information shock caused by innovation influences this response. The potential ideas of future studies can also examine industry-specific effects or the effects of the AI adoption on the firm-related long-term performance. This work would enhance the asset-pricing theory and enhance the understanding of the process of financial market adapting to technological change.

In conclusion, the rules mentioned in the chapter that emphasize the role of artificial intelligence are theoretical adaptation and the further evolution of the approach and the ability to interpret the market indicators carefully. Whereas this thesis is a solid case of turbulence in the short-term in the performance of the market in the aftermath of the introduction of the DeepSeek AI, it also underscores the relevance of future research to gain deeper insight into the cost of innovation by financial markets in more AI driven global economy.

5.4 Reflections

This section entails a critical evaluation of the overall procedure of the research as well as the limitations and benefits, challenges in compilation and accomplishment of research objectives. It also retrospects the effectiveness of the applied methodology and the development of competencies of the researcher.

These objectives of the research were set very initially and closely related to the overall purpose of the research, which was to determine the short-term consequences of the introduction of DeepSeek AI into the stock-market when used in a CAPM-based event-study model. These goals were well coherent in set and guided the data choice, methodology, and analysis. Overall, they are content since the empirical research has concluded the presence of abnormal returns, change of volatility and market specific (eliminating the initial research questions).

The outcomes were higher than expected and achieved in some areas. Although the introduction was expected to affect the cost of the stock, the abnormal returns were much higher and the example of cumulative abnormal returns showed that the classical asset-pricing models failed to explain the behaviour of the market in the case of the innovation shocks. This fact ensured that the study provided more scholarly input by lending credence to criticism on the CAPM and the significance of technological uncertainty in the financial markets.

The research was comprehensible and well carried out. The comprehensive quantitative analysis could only be done because secondary data was available, the event-study approach provided a sensible model that could be used to test the market response. However, such reliance on a single asset-pricing model, and a narrow events window were constraining. These were taken to light through tentative interpretation and careful treatment of the limitation of the study hence, there was rigour and transparency.

Some of the aspects of research process that were done well include the integration of theory and empirical research and comparison of NYSE and NASDAQ. Reflectively, the thesis would have included more asset-pricing models or global market analysis that would support the thesis. These extensions were shortened because of time constraint and availability of the data but could be healed in the future in order to enhance the generalisability.

It was also a sensitive task to the efforts and contribution of other writers and more specifically by using the available academic literature. It has already been assessed critically in previous publications, sources, and the historicalization of the research in already known arguments had been recognized. This only enhanced the importance of ensuring that one practiced ethically and in an academic way.

At the management and self-development level, the thesis enhanced the key competencies, namely the project planning, time management, data analysis, critical thinking. Coordination of time frames, milestones and feedback cultivation helped in personal investigation of skills. Future studies could develop the earlier pre-testing of methodology and internalize larger scale robustness tests. Overall, the overall process of researching was a productive experience and contributed to the further development of the academic and research-management skills.

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APPENDIX:

List of companies being studied.

Sr #	Company/Stock Name	Stock Ticker Symbol	Exchange/Market Name	Market Ticker Symbol
1	NVIDIA Corporation	NVDA	National Association of Securities Dealers Automated Quotations	NASDAQ
2	Broadcom Inc.	AVGO	National Association of Securities Dealers Automated Quotations	NASDAQ
3	Advanced Micro Devices	AMD	National Association of Securities Dealers Automated Quotations	NASDAQ
4	Microsoft Corporation	MSFT	National Association of Securities Dealers Automated Quotations	NASDAQ
5	Alphabet Inc.	GOOGL	National Association of Securities Dealers Automated Quotations	NASDAQ
6	ASML Holding	ASML	National Association of Securities Dealers Automated Quotations	NASDAQ
7	Micron Technology	MU	National Association of Securities Dealers Automated Quotations	NASDAQ
8	Vertiv Holdings	VRT	The New York Stock Exchange	NYSE
9	Constellation Energy	CEG	The New York Stock Exchange	NYSE
10	Taiwan Semiconductor	TSM	The New York Stock Exchange	NYSE
11	Marvell Technology	MRVL	National Association of Securities Dealers Automated Quotations	NASDAQ
12	Qualcomm	QCOM	National Association of Securities Dealers Automated Quotations	NASDAQ
13	Super Micro Computer	SMCI	National Association of Securities Dealers Automated Quotations	NASDAQ
14	Equinix	EQIX	National Association of Securities Dealers Automated Quotations	NASDAQ
15	Vistra Corp.	VST	The New York Stock Exchange	NYSE
16	Dell Technologies	DELL	The New York Stock Exchange	NYSE
17	Intel Corporation	INTC	National Association of Securities Dealers Automated Quotations	NASDAQ
18	Tesla, Inc.	TSLA	National Association of Securities Dealers Automated Quotations	NASDAQ
19	Apple Inc.	AAPL	National Association of Securities Dealers Automated Quotations	NASDAQ
20	Meta Platforms	META	National Association of Securities Dealers Automated Quotations	NASDAQ
21	Amazon.com	AMZN	National Association of Securities Dealers Automated Quotations	NASDAQ
22	Oracle Corporation	ORCL	The New York Stock Exchange	NYSE
23	Applied Materials	AMAT	National Association of Securities Dealers Automated Quotations	NASDAQ
24	KLA Corporation	KLAC	National Association of Securities Dealers Automated Quotations	NASDAQ

25	Lam Research	LRCX	National Association of Securities Dealers Automated Quotations	NASDAQ
26	Cisco Systems	CSCO	National Association of Securities Dealers Automated Quotations	NASDAQ
27	Skyworks	SWKS	National Association of Securities Dealers Automated Quotations	NASDAQ
28	Qorvo	QRVO	National Association of Securities Dealers Automated Quotations	NASDAQ