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# **High expectations, abnormal returns – Investigating the value of AI investment**

Perspectives from market efficiency and inefficiency

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**UNIVERSITY OF VAASA****School of Accounting and Finance****Author:** Tuomo Viitaniemi**Title of the thesis:** High expectations, abnormal returns – Investigating the value of AI investment: Perspectives from market efficiency and inefficiency**Degree:** Bachelor of Science in Economics and Business Administration**Major Subject:** Finance**Supervisor:** Rizwan Ahmed**Year:** 2026 **Pages:** 55

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**ABSTRACT:**

The purpose of this thesis is to examine whether abnormal returns (AR) can be observed in investments related to artificial intelligence (AI). This thesis also examines whether potential abnormal returns differ across sectors and how their occurrence has evolved during the 21st century.

Although Artificial Intelligence in a commercial sense is a rather new occurrence, there already is comprehensive scientific literature regarding the subject. Studies have employed various approaches to mapping AI investments and understanding their returns. This thesis aims to consolidate the findings and provide the reader with a broad perspective on the potential of AI in business, using clear language and comprehensive material.

The study is conducted as a literature review, synthesizing existing research on AI investments and applying financial theory to draw conclusions from the findings. Classical finance assumes that markets are efficient and prices reflect all available information, whereas behavioural finance suggests that investor behaviour, sentiment, and market dynamics can lead to deviations from expected returns. By analysing the literature through the lens of these two theoretical standpoints, this thesis aims to provide a clearer understanding on the returns and potential of AI, giving these two comparable stances to understand the matter from the viewpoint of financial theory.

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**KEYWORDS:** Artificial intelligence, Information technology, Abnormal returns, Expected returns, Stock prices, Investors, Performance, Efficient Markets, Behavioral finance

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**VAASAN YLIOPISTO****School of Accounting and Finance**

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**TIIVISTELMÄ:**

Tämän kandidaatintutkielman tavoitteena on tarkastella tekoälyinvestointien yhteyttä epänormaaleihin tuottoihin (AR). Tutkielmassa tarkastellaan myös, riippuvatko nämä potentiaaliset epänormaalit tuotot sektorista, ja onko niiden esiintymisessä nähty muutoksia 2000-luvulla.

Vaikkakin tekoäly kaupallisessa merkityksessä on varsin uusi ilmiö, on siitä olemassa jo laaja-alaista tieteellistä tutkimusta. Tutkimukset ovat hyödyntäneet moninaisia tapoja kartoittaa tekoälyinvestointeja ja niistä seuraavia tuottoja. Tämä tutkielma pyrkii koostamaan löydökset, ja tarjoamaan lukijalle laajaa perspektiiviä tekoälyn potentiaalista liiketoiminnassa, käyttäen ymmärrettävää kieltä ja kattavaa materiaalia.

Tutkimus suoritetaan kirjallisuuskatsauksena, kooten yhteen tekoälyinvestointitutkimusten löydöksiä ja soveltaen rahoitusteoriaa niiden ymmärtämiseen. Klassinen rahoitusteoria olettaa markkinoiden tehokkuutta, jolloin osakkeiden hinnat heijastavat kaikkea saatavilla olevaa informaatiota, kun taas käyttäytymistaloustiede rahoituksessa (BF) teoretisoi sijoittajien käytöksen, sentimentin ja markkinan dynamiikoiden johtavan eroihin odotetusta tuotosta. Analysoiden löydöksiä näiden kahden vastakkaisen näkökulman kautta, tutkielma pyrkii selittämään löydöksiä ja tekoälyn potentiaalia.

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**AVAINSANAT:** Artificial intelligence, Information technology, Abnormal returns, Expected returns, Stock prices, Investors, Performance, Efficient Markets, Behavioral finance

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## Abbreviations

**AI** – Artificial Intelligence

**LLM** – Large Language Model

**AR** – Abnormal Return

**CAR** – Cumulative Abnormal Return

**CAAR** – Cumulative Average Abnormal Return

**CAPM** – Capital Asset Pricing Model

**CS** – Computer Science

**GenAI** – Generative Artificial Intelligence

**DL** – Deep Learning

**NLP** – Natural Language Processing

**CV** – Computer Vision

**EMH** – Efficient Markets Hypothesis

**ETF** – Exchange Traded Fund

## 1 Introduction

Artificial intelligence (AI) has gained global attention. This has resulted in rapid change in operations in several industries. Fields such as finance, healthcare, entertainment, military, manufacturing and agriculture are among the many already taking advantage of AI (Rashid & Kausik, 2024). Not only is this the current state of reality, but also a constant state of evolution. AI-models are constantly improving, and it is highly likely that new, more capable models will replace the ones in use today, the potential of said technology being substantial (Hang, 2022, p. 56). Currently, AI is resulting in the fourth industrial revolution (Rashid & Kausik, 2024). Already, a special subset of Artificial Intelligence, called Large Language Models (LLMs), are capable of analysing, interpreting and generating human-like text in an exceptional method (Chen et al., 2024, p. 1762). For example, these models can inform patients in the field of medicine (Chen et al., 2024, p. 1788). Also, in finance, AI is continuously reshaping financial theoretical analysis (Chen et al., 2024, p. 1789). This evidence reflects not only verbal intelligence, but also rationality and capability to understand broad and complex contexts.

In business, there is already evidence that indicate positive correlation with firm's focus to artificial intelligence and net operating efficiency and net profitability (Mishra et al., 2022, p. 1194). Also, there are findings from Ante and Saggu (2025), that show significant, positive cumulative abnormal returns (CAR) on all simulated AI indices on their respective research. Of course, this potential has led to a surge of corporate AI investment and public interest (Ante & Saggu, 2025), to develop and distribute new AI models in an optimal method. This leads us to a key element of this study: certain sectors appear to exhibit higher demand for AI due to a closer alignment of AI systems and the specific needs of these domains (Chen et al., 2024, p. 1756). For example, general purpose, commercial LLMs, such as ChatGPT, remain promising in the field of finance, but their efficacy remains constrained due to the lack of specialization (Chen et al., 2024, p. 1790). On the other hand, in robotics, the efficiency of AI is highly dependent on its optimization to physical sensors. In Education, LLMs can be utilized as a supplementary teacher for students (Chen et al., 2024, p. 1792).

From these observations it becomes evident that AI meets the demands of various industries differently. Maximizing added value may necessitate domain-specific optimization and specialization, given the considerable variation in needs across sectors. Since AI affects different industries in distinct ways, its impact on expected stock returns is likely to vary across sectors. This reasoning is consistent with the Efficient Market Hypothesis, which states that prices quickly integrate new information (Fama, 1970, p. 385). In essence, this reflects the differential value creation in each domain. If investors fail to understand the potential gain in expected return, abnormal returns can manifest.

There is also some contrarian literature, that points out to the direction that news regarding AI investments could correlate negatively with firm's value, with drops in stock price after AI investments (Lui et al., 2020, p. 382). Again, in efficient markets this would mean that AI investments could lead to lower future cash flows or increased firm-specific risk. According to Capital Asset Pricing Model (Sharpe, 1964, p. 435) or its counterparts, increased risk would lead to higher required expected return and thus lead to higher level necessary for abnormal returns to emerge.

However, there is also theoretical framework for market inefficiency such as demand shock and price pressure (Schleifer, 1986). Also, there is behavioural theories that could explain gains and losses in stock prices that don't have a basis in changes in fundamental value. Behavioural theories hypothesize that market participants might not always act rationally leading to over- and underreactions in stock prices, trend extrapolation, heuristics (Tversky & Kahneman, 1974), loss aversion and disposition (Kahneman & Tversky, 1979).

These two perspectives, market efficiency and market inefficiency, provide a solid and comparative foundation for a comprehensive analysis of the results and will be employed in this thesis.

## 1.1 Purpose of the study

The purpose of this study is to examine how artificial intelligence (AI) adoption influences abnormal returns across the markets on the 21<sup>st</sup> century, with a focus in more recent developments. As discussed above, AI can deliver tremendous potential to various sectors and may be linked to increased net profitability and net operating efficiency (Mishra et al., 2022, p. 1194). As mentioned, there is multiple event studies analysing the correlation between focus in AI technologies and stock returns. Thus, the first hypothesis of the study is:

**$H_1$**  : The adoption of technologies involving Artificial Intelligence indicate abnormal returns.

However, because the automation needs and capacities to adopt artificial intelligence vary across sectors, it can be posited that the abnormal returns hypothesized also differ accordingly. Thus, the second hypothesis of the study is:

**$H_2$**  : The prevalence of abnormal returns of AI investments varies significantly across industries.

With an industry as dynamic as artificial intelligence itself, there could be significant changes during the progression of said technologies. If artificial intelligence is prone to changes in returns, this could indicate additional risk. Whether the focus on artificial intelligence means additional returns or not, market participants must be able to understand the potential as well as possible. Thus, the first research question is:

**$Q_1$** : Is there notable changes found during the time period of study?

The second research question link directly to the first research question, being:

**$Q_2$** : Is there any other additional factor found, that had impact on returns of AI?

Motivation of this study is reflected in the hypotheses. If investments in artificial intelligence truly indicate abnormal returns, and vary between sectors, it is crucial information to succeed in competitive markets. Whether it is management, investors, stakeholders, parties of interest or simply clients that could use this information on market dynamics, it helps making better decisions regarding value of a company or their product. Moreover, due to the topicality of the issue, the dynamics involved, and the ongoing changes, this research has clear general informational value, despite the background of reader.

## **1.2 Structure of the study**

At the start of the thesis, we introduced the reader to the subject, set hypotheses and explained the motivation and importance of this study. In chapter *Theoretical Framework*, we will examine Artificial Intelligence and key financial theory regarding the subject. We will explain what expected and abnormal returns are and how they are calculated. We will also discuss several financial theories, such as the Efficient Market Hypothesis and Behavioral Finance, and their connection to AI investments and returns. In Chapter *Abnormal Returns of AI technology*, we will perform the literature review. In Chapter *Empirical Investigation*, we will continue the review of results, apply critical analysis and try to make logical conclusions from the results found. Chapter *Conclusion* compiles the findings, presents possible limitations of the study and presents ideas for the future.

## **1.3 Time period**

This work focuses on the 21st century sample period (2000–present) to capture the full evolution of artificial intelligence-related technologies in financial markets. Although AI applications in business are a relatively recent phenomenon, the use of a long-time horizon allows for a comprehensive assessment of both early-stage technological development and more recent periods of rapid adoption. By employing an extended

sample period, the analysis is able to identify and highlight structurally meaningful changes over time, thereby enabling a more robust evaluation of the hypotheses concerning shifts in return dynamics and market behaviour associated with AI-related investments. Also, with a commercial product this novel and companies across the world racing to construct the best model, we aimed to achieve a large sample size to utilize observations from markets around the world.

## **2 Theoretical Framework**

To approach this subject from a financial perspective, we will here go over the theoretical principles of the subject. First, we will go over what artificial intelligence means, what its role is in this study, and then we will advance to the financial theory that is relevant to the subject.

### **2.1 Artificial Intelligence**

AI has a decades long history, with its conceptual framework dating back to the 1950's, with the famous Turing test to measure if a machine has the ability to deceive humans (Turing, 1950, p. 433). Contrary to a common misunderstanding, AI does not have a background in computer science (CS), but has a rather multidisciplinary background in mathematics, statistics and cognitive science, and already in 1980's, some use of AI could be seen across industries (Golec et al., 2025). Since then, artificial intelligence has been branching out to several different sections such as Deep Learning (DL), Generative AI (GenAI), Natural Language Processing (NLP) And Computer Vision (CV), with the introduction of more powerful computing processors in key position of making these advancements possible (Golec et al., 2025).

During more recent times in 2020s, AI has been developing to a form where it can finally simulate human cognitive processes with Generative AI models, which are able to produce new content. Since then, popular applications like ChatGPT and DeepSeek have emerged, which use Natural Language Processing (Golec et al., 2025). This technology allows the AI-model to process human language and respond in a humanlike manner, which in turn increases the commercial potential significantly, because it can finally be expected to understand typical human conversation, prompts and questions. Specifically, these popular models like ChatGPT, DeepSeek and Google Gemini are called Large Language Models (LLMs), which "are a special class of pretrained language models obtained by scaling model size and pretraining on large volumes of text data." (Kalyan et

al, 2024). As already in introduction is hinted at and later becomes evident, this advanced form of NLP technology has become point of attention in commercial AI.

As the paper from Golec et al. (2025) points out, artificial intelligence has branched out to several different areas with different strengths, with specific research fields focusing in robotics, autonomous vehicles, visual data with computer vision (CV), and deep learning (DL) employing a multi-layer structure to the neural network for the model to be more effective with complex data. This strengthens the argument that AI can have very different applications in different fields. For example, the research from Golec et al. found that ChatGPT required human feedback in healthcare services to increase accuracy.

### **2.1.1 The role of AI**

Because of the potential and subcategories of AI differing across industries, we approached AI in general sense, grouping all these different, but interlinked technologies appropriately under artificial intelligence as a whole. This allowed us to look at the impact of AI and its ability to generate abnormal returns in a holistic manner across sectors and maximise the sample of studies.

## **2.2 Efficient Market Hypothesis**

In 1970, Eugene Fama published a paper called *Efficient Capital Markets: A Review of Theory and Empirical Work*. In this paper he described an Efficient Market Hypothesis (EMH), which in essence means that stock prices reflect all available information and only react when new reaction is available (Fama, 1970, s. 383). This reflects an elastic nature of demand: because prices reflect solely on information about the business fundamentals, they won't react to changes in demand.

Fama did divide his hypothesis to three efficiency levels: weak, semi-strong and strong efficiency (Fama, 1970, s. 383). With weak efficiency alone, according to Fama's hypothesis, stocks would already reflect all historical information considering stock

prices and volume. Semi-strong form extends this to mean also all public information, such as earning reports and macroeconomic news. In strong form, also all private information is included and perfectly represented in the stock price. This means, that all insider knowledge, that only a few people would be aware of, would affect stock price accordingly.

This theory is clearly linked to abnormal returns because, the existence (or abundance) of abnormal returns dictates the efficiency of the market. If there truly are considerable, significant and systematically occurring abnormal returns, then the market must not be entirely efficient. However, EMH only claims that market prices reflect available data and new information is swiftly priced in securities. It does not claim that a specific estimation model for return is perfect. This means, that in theory, there could be possible to construct a model that is perfect on estimating returns. This model would have to take in to account all available information, and thus, could be impossible to generate. This is important notation for the sake of this thesis, as the existence of artificial intelligence could be so unpredictable in its evolution, that it would be extremely difficult to predict future growth rates, returns and risks of these companies. Nonetheless, to calculate the expected and unexpected (abnormal) returns, we will still need models to determine them. Even though the estimation won't be perfect, we can have an analytical and factual comparison and make rational conclusions about the financial potential of an asset.

### **2.3 Capital Asset Pricing Model**

Possibly the most widely used model, that relies in the principles of EMH, is Capital Asset Pricing Model (CAPM). It is generally accepted that it was firstly coined by William F. Sharpe in 1964, with his widely credited paper called *Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk*. As becomes evident from the time of publication, CAPM came to existence before the formal theory of EMH. Because Capital Asset Pricing Model bases on markets being efficient, we can note that at least some

kind of understanding of efficient markets must have been around before the publication of EMH.

In essence, CAPM is used to calculate the expected return of a security or portfolio. This is illustrated in Equation (1):

$$E(R_i) = R_f + \beta_i (E(R_m) - R_f) \quad (1)$$

**Equation 1.** Capital Asset Pricing Model (Sharpe, 1964).

Where:

$E(R_i)$  = expected return of asset  $i$

$R_f$  = risk – free rate

$\beta_i$  = beta of asset  $i$

$E(R_m)$  = expected return of market portfolio

$(E(R_m) - R_f)$  = market risk premium

Empirical studies on asset pricing typically use short-term government securities, such as three-month Treasury bills, as the risk-free rate. Beta ( $\beta$ ) measures the sensitivity of an asset's returns to the returns of the overall market.  $E(R_m)$  represents the expected return of the market portfolio, which reflects the average return of all investable assets in the market. The basic idea of CAP-model is, that the expected return of a security or portfolio is determined in relation to its sensitivity to market risk.

The reason why CAPM is so closely linked to EMH is, that CAPM assumes markets to be efficient. Because CAPM assumes the returns to base solely on systemic risk, it is in line with the EMH. For example, if returns were derived also from arbitrage, asymmetrical information or any other source, CAPM would have to include that variable into the model to be accurate.

### 2.3.1 Other forms to understand expected returns

Some studies use different models to calculate expected, and thus the abnormal returns, such as Market Model and Fama-French Three Factor Model. We will go over these two common models here.

#### 2.3.1.1 Fama-French Three Factor Model

In 1993, Eugene F. Fama and Kenneth R. French introduced an expansion to CAPM, called Fama-French Three Factor Model, in their joint work *Common risk factors in the returns on stocks and bonds*. This model is a clear derivation from the classic model, adding size and value factors to the equilibrium. This is illustrated in Equation (2):

$$E(R_i) = R_f + \beta_i \cdot (E(R_m) - R_f) + s_i \cdot SMB + h_i \cdot HML \quad (2)$$

**Equation 2.** The Three Factor Model (Fama & French, 1993).

Where:

$s_i$  = Sensitivity to size factor (SMB)

SMB = Return of small minus big portfolios

$h_i$  = Sensitivity to value factor (HML)

HML = return of high minus low book-to-market portfolios

As shown in Equation (2), The Three Factor model contains the classic CAPM combined as one component, adding these new variables resulting in a three-component model. In this context, small minus big simply means the return difference of small-cap and large-cap stocks on the market, or simply, the size premium. Likewise, high minus low means the return difference between high and low book-to-market stocks or simply value premium.

All stocks often are growth and large cap companies, so size and value factors can be very beneficial on understanding value, in comparison to the classic CAPM only measuring the expected return based on the systemic risk. Here we can also highlight the basic

problem of financial modelling: no model can be concluded perfect, and we can only approximate the expected return of an asset.

### 2.3.1.2 Market Model

When the goal is to calculate expected returns, one additional model is called the market model. It is widely used in event studies that investigate market returns, and it is closely related to the CAPM. This model was first presented as “single-index model” by William F. Sharpe, in his paper *A Simplified Model for Portfolio Analysis* (1963). Later, this model became more widely known as market model. Notably, as Sharpe presented CAPM in 1964 and single-index model in 1963, the market model became into existence before the CAPM. The Market Model is illustrated in Equation (3):

$$E(R_i) = \alpha_i + \beta_i E(R_m) \quad (3)$$

**Equation 3.** Market Model (Sharpe, 1963).

Where:

$R_i$ : return of asset  $i$

$E(R_i)$  : expected return of asset  $i$

$R_m$ : return of the market portfolio

$E(R_m)$  : expected return of the market portfolio

$\alpha_i$  : asset  $i$ 's return independent of the market

$\beta_i$  : sensitivity of asset  $i$  to the market return (beta)

$\varepsilon_i$  : random error term

Note, that random error term is not visible in Equation (3). This is because it is assumed to be 0 in the presented form of expected returns, which removes random noise from the equation. This is important in the context of analysing abnormal returns, because it allows any deviation of realized returns from this baseline to be interpreted as abnormal returns.

A comparison between the market model and the CAPM reveals clear distinctions. Market model is simply an empirical model that bases on observed data, where alfa and beta are estimated from historical performance. This makes it a model that bases on realized facts and doesn't require assumptions on market efficiency. On the other hand, CAPM is a theoretical model in nature, and bases on assumptions on market being efficient: it assumes perfect competition, risk-free rate and rational agents on the market. Here we come to another clear distinction between the models: CAPM doesn't allow the existence of alfa, while Market Model has it as a core component. This deviation is often referred as abnormal returns in event studies and reflects again how CAPM model simply assumes market efficiency while Market Model does not. However, abnormal returns on a short period cannot be calculated by simply solving alpha, as alpha is a constant in the equation, calculated from historical data. Specifically, alpha can be described as the historically estimated average annual abnormal return of an underlying asset.

## 2.4 Abnormal Returns

As already discussed, abnormal returns are calculated as the difference between realized returns and estimated returns. Finally, we can illustrate the simple formula for abnormal returns in Equation (4)

$$AR_{it} = R_{it} - E(R_{it}) \quad (4)$$

**Equation 4.** The formula to calculate abnormal returns.

Where:

$AR_{it}$  = abnormal return of the asset at time  $t$

$R_{it}$  = realized return of the asset at time  $t$

$E(R_{it})$  = expected return of the asset at time  $t$

It is already mentioned that the theoretical idea was laid by EMH, however, at least one of the first papers to use abnormal returns as a measure in academic context was done

by Fama et al. in 1969 in their joint work *The Adjustment of Stock Prices to New Information*. On this paper they analysed how stock prices reacted to news regarding the company, such as changes to dividend policy or mergers & acquisitions, using the market model (3). Event window was several days before and after the news. For example, news regarding dividends had event window of **[-10, 10]**, which mean that event day is classified as **[0]** (in this case the news), and negative and positive numbers inside the brackets mean how many days prior the event window started, and how many days after the event window lasted. The alpha and beta were calculated with an estimation window of several months before the event study. This is a classic example of use of abnormal returns in an event-based analysis, and multiple studies like this are later mentioned in the literature review regarding abnormal returns of AI Investment. However, abnormal returns can also be calculated as cumulative abnormal returns (CAR) or cumulative average abnormal returns (CAAR) from a longer period to capture a persistent anomaly. These ways of quantifying are also present in the literature review, to capture comprehensive, long-lasting effects about the studied subject, not only small window changes.

It must also be highlighted, that the abundance of abnormal returns does not mean the abundance of returns. For example, as Equation (1) indicates, the higher the market risk ( $\beta$ ) is, the higher the expected return will be. This means, that artificial intelligence technologies can be very fruitful from the point of view of returns without significant abnormal returns, but this would be accompanied with higher level of risk. Nonetheless, we can also see from the same relation, that if this mechanic stays symmetrical, no abnormal returns are observed and thus, artificial intelligence technologies wouldn't bring additional value to the investor in comparison to the market portfolio. In this case, the higher level of risk ( $\beta$ ) could simply be obtained with debt leverage. This highlights the importance of abnormal returns when analysing the potential of investing in a specific type of security.

## **2.5 AI & Market Inefficiency**

Also, many theories regarding market inefficiency exist. To have as comprehensive picture of market dynamics regarding the subject, the thesis gets an important, contrasting viewpoint to the case by highlighting these theories and taking advantage of them in the critical analysis. Here we will go over some of the key theories regarding the subject.

### **2.5.1 Demand Shocks & Price Pressure**

As already mentioned, Efficient Market Hypothesis assumes almost, if not perfect elasticity in market demand. In his paper *Do demand curves for stocks slope down?* (1986) Andrei Schleifer presents an opposing idea: big agents on the market can make demand shocks and thus have significant price pressure on the stock prices upon a large transaction, driving it up when buying and down when selling. This happens because when the transaction is big enough in size, the sell positions on the market can't cover the amount and thus some number of securities must be bought on a higher price. Of course, this effect is stronger in low liquidity environments, such as with small companies. This result suggests an important implication in comparison to the Efficient Market Hypothesis: the fundamentals of the company have not changed, yet the price has.

In context of AI Investments, there could be certain key moments of demand shock: liquidity issues in small AI-startups, company being included to an AI-Index or ETF or large investments from institutions due to high potential of AI technology. In all these cases agents on the market are acting rationally, however, the prices could experience significant changes.

### **2.5.2 Prospect Theory**

The field of behavioral finance (BF) gives several ideas to market participants not acting in a rational manner. In 1979, Daniel Kahneman and Amos Tversky presented Prospect Theory. The idea behind the theory was, that some investors might in fact have

asymmetrical orientations to risk, rather than rationally maximising expected return (Kahneman & Tversky, 1979, p. 264). This would mean, that some people are risk-averse, and some risk-seeking. For example, a risk-averse market participant could neglect a deal of clear positive expected return, if risk is involved. In other words, the participant would be ready to lose money to not expose their assets to risk. At the same time, some participants would be ready to take bets with negative expected return, just to get the exposure to risk. Of course, we know multiple examples from the real world to both scenarios, like insurance business for risk-averse, and general gambling for risk-seeking participants.

Nonetheless, Prospect Theory also describes that this mentioned orientation to risk changes depending on the situation: when investor is in a loss position, they are risk-seeking to gain back sunken costs, and when in a gain position, they exhibit more risk-aversion to realize the gains made (Kahneman & Tversky, 1979, p. 279). Once again, we can make an important notion with AI investments: if news regarding AI investments systematically generate abnormal returns, according to prospect theory, market participants would be willing to close those gaining positions asymmetrically in comparison to losses in similar positions: this would have a diminishing effect on both negative and positive abnormal returns, as gaining positions are closed prematurely and losing positions are increased irrationally, resulting once again in price pressure, driving the prices of a security up.

### **2.5.3 Heuristics**

Before Prospect Theory, Kahneman and Tversky had already presented another theory about irrational market participants. In 1974, they published *Judgment under Uncertainty: Heuristics and Biases*. In this theory, they presented several heuristics, that represent cognitive shortcuts to complex problems, leading in irrational decisions. In their 1974 work, they mentioned representativeness, availability and anchoring and adjustment as heuristics. The paper mentions several biases, that are portrayed as results of using heuristics. Representativeness means, that investors assess probabilities

from the basis of stereotypes, or memorable and typical occasions (Kahneman & Tversky, 1974, p. 1124). Availability means, that the assessment is made based on availability of data regarding it, not the accuracy of said data (Kahneman & Tversky, 1974, p. 1127). Anchoring and adjustment means relying too much on previous known occasions, and thus having insufficient adjustment to new, differing data in their decision making (Kahneman & Tversky, 1974, p. 1128). In Chapter *Empirical Investigation on findings*, we will have several examples of biased action due to heuristics, as these theories can be argued to link directly to possible inefficient market dynamics in AI investment.

### **3 Abnormal Returns of AI technology**

Building on the theoretical framework, the empirical analysis draws on previous studies that have applied CAPM, the Fama–French three-factor model, and the Market Model to calculate abnormal returns. Some studies focus more on a specific type of AI, such as LLMs, and in these cases, this is clarified.

The method of study on this thesis is literature review. The following section reviews scientific literature that relates to abnormal returns of artificial intelligence. Here, we will go into what methods have been applied to analyze the market regarding AI involvement, investment, risk and return. Lastly on this section we will compile the results.

#### **3.1 Engagement in AI**

To understand firm's engagement with Artificial Intelligence, there must be some method of quantifying it. One way of doing this is looking into the 10K filings of enterprises. 10K filings are detailed annual reports required in the U.S. If the firm has real focus on artificial intelligence, it must disclose it in these annual reports. In their respective event study, Ante and Saggi (2025) analyzed these filings during the period of 2011-2023, with a sample of 3 395 firms listed to the NASDAQ stock exchange. They used binary indicators and weighted AI scores to understand every company's involvement in AI. After this, they formed four AI-indices, an equally weighted index (AII), a size weighted index (SAII) and two indices that were time-discounted. The time discounted indices gave more weight to newer AI mentions in 10K filings, with Time-Discounted AI Index TAI105 using a discount factor of 0,5 and TAI15X a discount factor of 5. This means that both indices value newer AI mentions more than older ones, but with TAI15X the discount of older mentions is drastically greater. As a control group, they used a basket of 2541 stocks, that were not controlled to be AI focused or not. Time frame was centered to the inception of ChatGPT. Furthermore, market model was used in calculating the possible abnormal returns, with an estimation window of 251 trading

days before ChatGPT to estimate alfa ( $\alpha$ ) and beta ( $\beta$ ) for the market model. Event window used was 61 trading days from the launch of ChatGPT 3.5 on 30<sup>th</sup> November 2022. Although prior ChatGPT models like GPT 3.0 did exist before this launch, the prior models were available for only testing groups and the launch of GPT 3.5 was the first ChatGPT model available for public audience to use (History, 2022).

What was found in the research by Ante and Saggiu (2025), was that all the AI indices delivered statistically significant mean daily abnormal returns during the event window. The largest average abnormal returns were tracked from SAII (0,34 % per day), while all the other indices, AII, TAI105 and TAI15X all brought 0,27 % mean daily abnormal returns. The impact of these abnormal returns becomes more evident when looking at the cumulative abnormal returns from the whole event window of 61 trading days:

**Table 1.** Abnormal returns of the four AI-indices (Ante and Saggiu, 2025).

AI Indice	Description of indice	Mean Daily AR (%)	CAR (%)
AII	Equally Weighted	0,27	16,35
SAII	Size-Weighted	0,34	20,97
TAI105	Time-Discounted (discount factor of 0,5)	0,27	16,19
TAI15X	Time-Discounted (discount factor of 5)	0,27	16,40

Mishra et al. (2022) used a similar approach of studying 10K filings in *Artificial intelligence focus and firm performance*. They found a correlation between AI engagement and firms efficiency measures. The results indicate that engagement with AI increased employee costs but also improved net efficiency in measures such as return on sales, return on marketing investment, and net profit per employee (Mishra et al., 2022, p. 1184). This suggests that AI focus not only creates abnormal returns but also has significant changes inside the enterprise operations.

### 3.2 Investing in AI

There is also an argument to be made, that all engagement in AI does not necessarily mean investment in AI. This was already discussed in the paper by Ante & Saggi (2025) as *AI washing*, which in essence would mean exaggerating the firm's involvement with said technologies. In comparison to the method of analyzing 10K filings, Lui et al. (2022) used a different approach when studying abnormal returns of AI. They analyzed announcements from 62 firms, in an event study containing announcements of investing into artificial intelligence, during the period of 2015-2019, obtaining 119 observations from the sample firms in total (Lui et al., 2022, p. 379). The model used to calculate the expected returns was no other, than the CAPM (Lui et al., 2022, p. 380).

Multiple event windows were used, ranging from one day prior to the announcement to one day after the announcement, and differing combinations of these days. The most significant price change was found to happen during the day of the announcement. No information leakage prior to the announcement was found, and the mean market reaction of these observations during the announcement day of -1.71% (Lui et al., 2022, p.382). In addition, all different event windows show negative abnormal returns:

**Table 2.** Mean AR of the 119 observations from 62 firms (Lui et al., 2022, p.382).

Event Window	[-1]	[0]	[+1]	[-1, 0]	[0, +1]	[-1, +1]
AR (%)	-1,66	-1,77	-1,51	-3,44	-3,28	-4,94

The key results suggest a drastic difference to significant positive abnormal returns found in the newer paper by Ante and Saggi (2025). We also see the interesting distinction between the two studies, as the paper by Lui et al. studies the pre-ChatGPT era, while Ante and Saggi start their event window from the launch of public ChatGPT. However, we must acknowledge the drastically smaller sample size and different method of

constructing the sample in comparison to the paper of Ante and Saggi (2025). Also, we must note that this research investigated immediate reactions to the news and not a longer period.

Interestingly, even though no information leakage was found in the study, the sample firms experience similar negative abnormal returns before the announcement. This could indicate that the news didn't have significant impact on AR, but the sample firms were giving weak returns in general. There is some proof to this idea: the study found that negative abnormal returns were especially strongly associated with firms with weak IT capabilities and weak financial healthiness. From the principles of Efficient Markets (Fama, 1970), these findings indicate that businesses of low IT capability or poor financial status could face additional risk or decreased future cashflows when investing into artificial intelligence. Here we also see some evidence to our second hypothesis, that all businesses in various sectors won't experience similar abnormal returns with AI investments, and for the firm to get maximum benefit of AI, it must be constructed in a certain way.

### **3.3 ChatGPT Impact**

As we already argued, there is indications that ChatGPT could have an impact on stock market returns. We found a study to analyse this idea more thoroughly; *A Trillion Dollars Race — How ChatGPT Affects Stock Prices* (2025) by Marcin Pietrzak investigated this possible phenomenon. In their research, they performed an event study focusing in ChatGPT related news by U.S. companies, with a focus in IT and technology firms. However, other sectors such as finance, energy, and industrial sector were included for comparison (Pietrzak, 2025, p. 7). The final sample was 142 announcements from U.S. listed companies, and they were observed on time period of five months, from 1<sup>st</sup> of January 2023 to 31<sup>st</sup> of May 2023 (Pietrzak, 2025, p. 4). As already noted, this is well in the era of public ChatGPT 3.5 model, which launched in November 2022. Once again, Market Model (3) was used to calculate expected returns, with a 250-day pre-event window to estimate alfa and beta from S&P500 daily returns (Pietrzak, 2025, p. 4). Like

in the study of Lui et al. (2022), the event day [0] was set to be the day of announcement, with various event windows. The results are presented in the following table:

**Table 3. Mean abnormal returns of the 142 observations (Pietrzak, 2025).**

Sector, Event Window	[-1, +1]	[-3, +3]	[-5, +5]
IT / Technology AR (%)	+1,8	+2,4	+2,7
Finance AR (%)	+0,2	+0,3	+0,4
Energy / Industrial AR (%)	-0,1%	0,0%	+0,1%

The evidence from the study shows a drastic change in returns of IT and Technology firms to the comparison groups. Finance and Energy / Industrial seem not to be gainers of ChatGPT news, while IT and Technology had significant abnormal returns. In fact, there seems to be no significant impact of ChatGPT news on Finance, Energy or Industrial stocks. These observations provide useful context for the findings of Liu et al. (2022) and Ante and Saggiu (2025). ChatGPT seems to be having a real impact on AR, and once again, firms with weaker IT capabilities tend to make lesser abnormal returns. Nonetheless, in contrast to the research by Liu et al. (2022), negative AR effects are almost nonexistent.

### 3.4 Different sectors and AI

On this section, we will advance to more sector-specific analysis on AI-related returns. We found several studies regarding a specific sector, and as the evidence on Chapter *ChatGPT Impact* indicate, there could be real differences from one sector to another. These studies are also in a key position to provide results for H<sub>2</sub> and Q<sub>2</sub>.

#### 3.4.1 AI as an industry

As artificial intelligence is a subset of information technology, the AI industry itself may experience significant abnormal returns. According to a paper by Chou et al. (2026), artificial intelligence industry was found to have made significant abnormal returns from 2018 to 2024. Their sample universe was the stock exchange of Taiwan and 11 OpenAI's

technological announcements during the mentioned period. What makes the position of Taiwan interesting, is that according to the study, as of 2023, Taiwan accounted for more than 60% of the world's chip only factors and nearly 90% of the most advanced chips are made in just a few places Chou et al. (2026).

Again, an event study was constructed, where they studied the stock reactions of *AI Concept firms* and *Matched firms* to OpenAI's announcements. In the research, an AI Concept firm is an organization which is directly tied to artificial intelligence itself, or to a concept involving artificial intelligence. In essence, matched firms act as a control sample, and mean companies with no such ties to AI. Market model was deployed to estimate expected returns with an estimation window of 200 trading days before the event of an announcement. Furthermore, event window was constructed to span from the event day [0] to 5 days after the announcement. All the 11 announcements regard the ChatGPT models, with starting from the launch of GPT1 in 11<sup>th</sup> of June 2018, and spanning all the way to 18<sup>th</sup> of July 2024, with an update to ChatGPT 4o Mini model. Moreover, the announcements are classified as "new" or "update", regarding the fact if the announcement is about a launch of a new model or an update to older model. Finally, four portfolios were constructed: AI-New, AI-Update, Matched-New and Matched-Update. These portfolios basket all the observations to one of the indices depending on the category of the firm and announcement. In total, there were 764 observations of AI Concept firm stock reactions, and 954 observations of Matched firm reactions to the news regarding ChatGPT models. Importantly, this is an inverted way of measuring returns, as this research investigated firm's price changes to announcements originating from outside the firm (announcements from OpenAI), not to announcements by the firm itself.

Results indicate significant differences of cumulative abnormal returns (CAR) with AI Concept firms and Matched firms. Also, this difference stays consistent and intensifies after the event for several days. The key results by Chou et al. (2026) are presented in the table below:

Indice	Observations	AR[0] (%)	CAR[0, +1] (%)	CAR[0, +5] (%)
<b>AI-New</b>	274	0,37	0,8	1,67
<b>AI-Update</b>	490	0,37	0,15	0,25
<b>Matched-New</b>	341	0,24	0,02	-0,12
<b>Matched-Update</b>	613	-0,02	-0,32	-0,45

**Table 4.** Mean AR of the four constructed indices (Chou et al., 2026).

Table 4 indicates that when OpenAI made an announcement regarding a new ChatGPT-model, the difference in cumulative abnormal returns of AI-firms and control group was 1,79 % on a period of event day to five days after the event. News regarding an update to older model brought a difference of 0,7 % on a same period. In both cases, AI-firms were the clear winner.

However, we must note that of the 11 events tracked by Chou et al. (2026), there is 4 events that clearly stand out with cumulative average abnormal returns, on period of **[0, +5]**. These are Events 5, 7, 8 and 9. These were the only events bringing over 2 % of CAAR. Event 5 was an update to GPT 3, Event 7 was the launch of public LLM-model ChatGPT 3.5, Event 8 announced ChatGPT Plus as a subscription and Event 9 published the next model GPT4. Here we make the interesting notion towards prior studies, that significant CAAR's are detected prior to GPT3.5 going public. However, GPT3.5 remained giving strong returns also. It can be theorized that even though GPT3 was not public, it already presented strong abilities and its market changing potential was anticipated before the public launch.

### 3.4.2 Finance

In Chapter *ChatGPT Impact* we saw some evidence that AI incidents could have no meaningful impact on finance stock returns (Pietrzak, 2025). However, the research didn't have clear focus in finance and used the sector as a comparative category. In their paper *How artificial intelligence incidents affect banks and financial services firms? A*

*study of five firms*, Durongkadej et al. (2024) studied the impact of AI incidents on banking and the financial industries. This time, to calculate abnormal returns, Fama-French model was deployed. As a sample, they only had 5 Finance firms that faced a notable AI incident. The results indicate a significant, -21.04 % negative cumulative abnormal return on a period of one day before the event to one day after the event day.

Key problems with this study were found. Firstly, there is no clear definition for the mentioned "AI Incidents" in the paper. With a sample this small, and negative returns being extreme, it would be key information to know the nature of said tracked incident. In fact, a direct quotation from the research goes as: "Out of five companies, two companies went bankrupt or on the brink of bankruptcy after the AI incidents" (Durongkadej et al., 2024). In a deeper analysis, in fact as per 2026, two of the sample five experienced a crisis and don't exist as an independent company. First, Knight Capital Group was acquired by Getco LLC in 2012 (CNBC, 2012), and Republic Bank was acquired by FDIC in 2023 (Federal Deposit Insurance Corporation, 2023). The reasons behind these acquisitions give important context: Knight Capital Group collapsed due to a system glitch in automated algorithmic trading, resulting in millions of wrong orders fulfilled (Kapadia & Linn, 2019). The ultimate failure of First Republic Bank was caused by rapid deposit withdrawal, caused by contagion of other bank failures (bank run), accompanied by poor financial state and risk management (Federal Deposit Insurance Corporation, 2023).

The findings indicate key problems with the study: the collapse of these two institutions, which represent 40% of the small sample, have significant result-distorting features with collapsing stock prices, and the relationship of the said "AI Incident" and real life AI technologies can be clearly disputed: while the algorithmic fail of Knight Capital can be loosely argued to have some ties to emerging AI, the fate of First Republic Bank seem to have no clear ties to real investment to AI technologies. Although this study could help analyze critical errors in banking, concerns about the validity of the AI incident data lead to the rejection of its results.

### 3.4.3 Data Centers

The implementation of artificial intelligence requires significant computing power, as according to the theoretical framework, the advancement of artificial intelligence was only possible after more powerful computing chips (Golec et al., 2025). This computing is generally done in specialized data centers, which are “indispensable” to the functioning of the digital economy and the advancement of artificial intelligence, according to research from Davinder K. Malhotra, Ivar Kirkhorn and Frank Ragone (2025). In their analysis, they looked at the possible abnormal returns of Data Center ETFs from January 2000 through December 2024. They suspect the growing demand of data centers is exactly due to need for computing power for development and processes of Artificial Intelligence (Malhotra et al., 2025, p. 449). The model used on determining abnormal returns was an expansion from the traditional Fama-French: a five-factor model accompanied with momentum as an additional variable (Malhotra et al., 2025, p. 451). As noted in the theoretical framework, this type of model could be more accurate on describing the expected returns of sectors involved heavily in AI.

Despite the appealing story of Data Center ETFs, they found negative mean monthly abnormal returns (-0,05 %), when examining the entire event period of the study (Malhotra et al., 2025, p. 459). This small change was found to be statistically insignificant. However, the monthly abnormal returns intensified to -0,41 % per month during the COVID19 -pandemic period of 2020-2024, and here, statistically significant underperformance was detected.

Additionally, the paper mentions, that “Data Center ETFs produced a mean monthly return of 0,65 percent over the sample period of January 2000 to December 2024, much lower than the S&P 1500 IT Index (0,91 percent)” (Malhotra et al., 2025, p. 453). It is also noted in the study that despite making slightly lower returns, they make up for it with slightly reduced volatility. Shortly, Data Center ETFs were found to provide no additional

value during the 2000's, while slightly underperforming during the COVID19-era (Malhotra et al., 2025, p. 453).

#### **3.4.4 Platform Enterprises**

Digital platform-based business models create ecosystems of external partners, who contribute to innovation and increase the overall value of the platform (Gawer & Cusumano, 2014, p. 417). Examples of platform-based business models could be Amazons marketplace, Facebook and YouTube. Recently, a growing number of companies providing digital platform services have started to heavily invest in AI (Zhang, 2025). The motivation behind this is the capability for intelligent technologies to connect, develop and govern the enterprise. Furthermore, AI is currently “transforming services by providing personalized solutions, enhancing customer experience, and reducing operational costs” (Kim, 2024, p. 851). Because platform businesses connect owners, external partners, and customers, they require personalized solutions and high-quality customer experience. From this we can argue that AI technologies seem to provide real, fundamental value to the business model. As evidence of this, all three companies mentioned, Amazon, Meta (Facebook) and Alphabet (Google) exhibit rapid investing in their own AI technologies (Gupta et. al., 2025, p. 57).

To analyze this in the perspective of abnormal returns, we found a study from Yaodong Xie (2024) In their paper *The Analysis of the Abnormal Return Rate of Platform Enterprises*, they analyzed Abnormal Returns in the Chinese market. Their study selected 174 platform enterprises, and analyzed their possible abnormal returns (AR), during 214 technical introduction announcements during the period of 2020-2024. Again, market model was used, with 200 trading days before the event as an estimation window. The paper states the following:

*“Combined with the market efficiency hypothesis, this paper revealed that on the day of the introduction of new ai technologies, the market would produce a significant positive*

*response, with an average abnormal return of 0,011 and a positive rate of 56%.” (Xie, 2024, p. 155)*

For the sake of this thesis, the findings are significant. The time period is centered to the commercial NLP models and show significant positive AR (1,1%) during the day of an announcement. Again, findings show clear positive abnormal returns from tech-oriented companies regarding technology development.

### **3.4.5 Crypto Currencies**

There is also some empirical evidence of abnormal returns in AI driven crypto currencies. Ante & Saggi studied the returns of AI-related crypto currencies with again, a period starting from the launch of ChatGPT 3.5, in their study *The Influence of ChatGPT on Artificial Intelligence Related Crypto Assets: Evidence from a Synthetic Control Analysis* (2023). They identified significant “ChatGPT effects”, with extremely high returns of 35,5 % in the two-month period after the launch of ChatGPT. By contrast, it must be acknowledged that these were tracked as general, not abnormal returns, combined with the nature of high volatility and thus high expected return of cryptocurrencies, but these extreme returns remain still significant, as per study, they were caused by the launch of ChatGPT.

There is also a working paper which strengthens the perception of high AI AR in the field of crypto: *“We reveal significant abnormal returns for AI tokens after the launch of ChatGPT, up to 41% over the course of two weeks. Moreover, 90% of tokens exhibit positive abnormal returns (Ante & Demir, 2023).*

Again, findings exhibit a notable shift to positive abnormal returns after the launch of ChatGPT. From the point of view of efficient market, this would mean that NLP models especially contain extra value to investors. We found one additional study that makes a similar finding: *Do AI incidents and hazards matter for AI-themed cryptocurrency returns?* by Wang et. al. (2025). They studied how negative incidents and hazards affect

cryptocurrency returns. Their findings highlight once again the impact of NLPs: negative AI-related news did not have significant impact on cryptocurrency returns before the launch of ChatGPT 3.5. However, after the launch, returns of AI-themed cryptocurrencies started to have negative correlation with said negative incidents and hazards. Here we make another significant finding that the advancements of commercial LLM models could have impact also to negative performance. Relevance of impact like this on the overall market remains unknown.

### **3.5 Impact on risk**

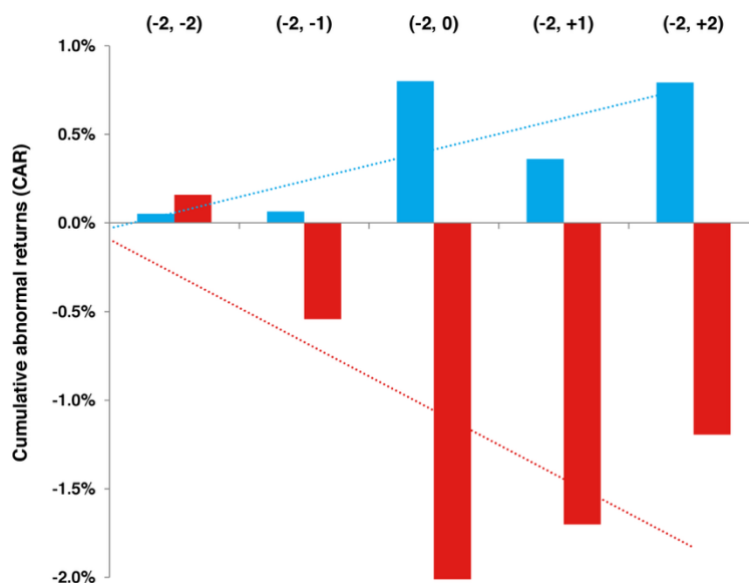
There is some literature backing the theory of artificial intelligence technologies reducing risk: *Artificial intelligence innovation and stock price crash risk* (2024) by Zhang et. al found, that artificial intelligence innovation reduced the risk of a sudden crash of stock price. One explanation mentioned in the study was that artificial intelligence technologies improved corporate governance significantly, which made these companies more robust to stock price crashes.

There are several arguments in favor that, if the risk for downside reaction diminishes, it could induce some AR. For example, investors could react positively to the new, unpredicted information of lesser risk, and thus create abnormal returns, at least over a short period of time. By contrast, there is another interesting perspective on the issue. As introduced in Chapter *Theoretical Framework*, The Market Model normally has  $\varepsilon_i$  present to consider idiosyncratic risk, which in essence means firm-specific risk. This kind of reduction in risk of downside would directly impact  $\varepsilon_i$ . However, in expected return form  $\varepsilon_i$  is not present, and thus, these changes would be present as the difference of realized gains and expected gains, or in other words, as abnormal returns. From the perspective of the market model, these kinds of reductions in risk would directly induce abnormal returns. However, this phenomenon is model specific, as for example, the CAPM only considers the systematic risk, and these changes would not necessarily induce abnormal returns.

### 3.6 Technological Advancements in Medicine

There are several studies that have found positive effects of artificial intelligence in the field of medicine. For example, artificial intelligence technologies have been found to be offering “significant advantages in addressing the challenges of classical drug discovery and development” in several forms, such as analyzing large datasets, optimizing chemical leads, aiding in early clinical trials and helping in determining which biomarkers forecast the disease and which forecast treatment response (Ocana et al., 2025, p. 10). In short, it becomes very evident that there is clearly added practical value of AI in drug development and overall business. With this added value, businesses are more effective in developing new medical products.

Event study by Hwang (2013) investigated the abnormal returns of drug companies during announcements about clinical drug trials and developments. The sample consisted of 24 public result announcements regarding 23 clinical trials (Hwang, 2023, p. 5). In a positive event, the drug meets expectations for efficacy and safety; in a negative event, it does not. The results indicate that positive events tend to create positive abnormal returns while negative events tend to create negative abnormal returns.



**Figure 1.** Abnormal Returns of positive (blue) and negative (red) announcements, on multiple event windows (Hwang, 2013).

The combination of findings by Hwang (2013) and studies on Artificial Intelligence aiding in drug development do indicate that AI technologies could induce abnormal returns in the pharmaceutical and medicine industries. Nonetheless, more thorough event studies are needed with a clear focus in AI announcements in medicine and pharmaceuticals.

### **3.7 Working papers**

In commercial sense, the field of Artificial Intelligence is still very young. Even though the theoretical framework dates back several decades, public models like ChatGPT and Gemini are only a few years old. Here, we will cover additional working papers as additional evidence regarding the subject.

#### **3.7.1 UK market**

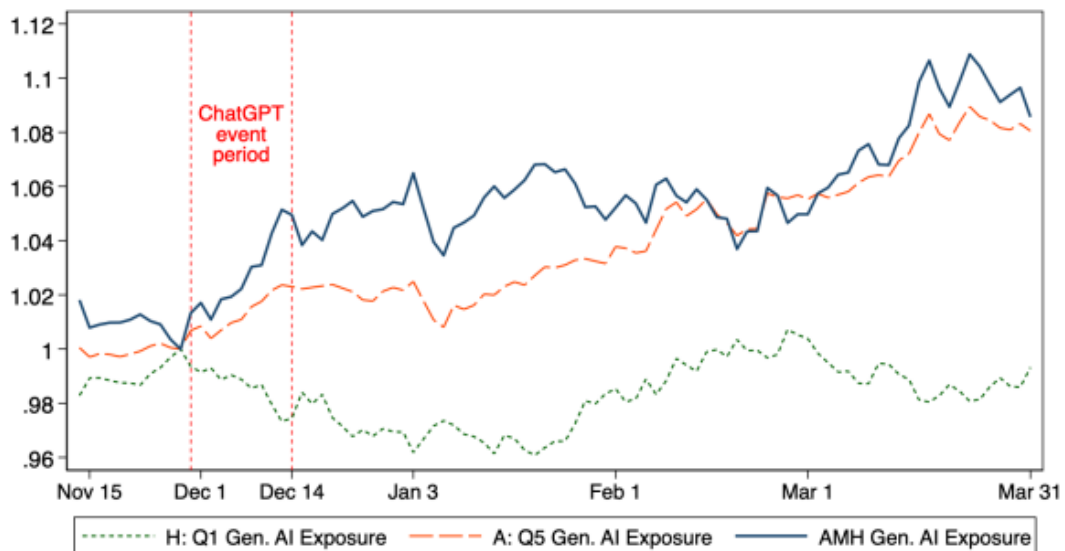
A research conducted by Kurter & Bhatti (2024) investigated abnormal returns of AI announcement in the UK market. Sample analyzed was 138 AI announcements from 53 firms, during the years 2019-2023. Overall, they didn't find statistically significant (+0,114%) impact of AI investment to abnormal returns, but when looking specifically to different sectors, they found that healthcare industry received significant (+1,6%) abnormal returns, in comparison to the IT and business services -sectors in a period of 2 days before to two days after the announcement (Kurter & Bhatti, 2024, p. 17). Also, high credit score firms face significant (-1,9%) negative abnormal returns compared to the low credit score firms in a period from five days before the announcement to five days after the announcement. In addition, the study found a size effect that implies larger firms facing more negative returns.

In this working paper we once again see clear evidence of a firm factor. According to this study, an ideal gainer of artificial intelligence investment would be a small, low credit score firm from the healthcare industry. However, it must be pointed out that the study

didn't control if these metrics had an impact to each other, i.e. if a medical company would receive a negative AR impact from AI-investments when it specifically had low credit score or was small in size.

### 3.7.2 Generative AI and Firm values

A study conducted by Eisfeldt et. al (2025) investigated the difference of cumulative abnormal returns (CAR) of firms with different exposures to AI. Specifically, they constructed five value-weighted portfolios with different exposures of occupation to artificial intelligence technologies. Findings once again point to the significant positive abnormal returns of AI. Their portfolio, that invested into the quantile of largest AI exposure and sold short the lowest exposure quantile, received significant abnormal returns. Another important finding was no significant abnormal returns prior to the launch of ChatGPT. Daily abnormal return variance was 0,45% during the event window, depending on the firm's occupation exposure to AI.



**Figure 2.** CAR of firms before, during and after the launch of ChatGPT (Eisfeldt et. al, 2025).

The results once again support the positive CAR impact after the launch of ChatGPT, and the insignificance of AI-model investment to abnormal returns prior to the launch of

ChatGPT. The study argues that these findings support the idea that the emergence of public LLM-models truly had a significant technology shock to the market. We must point out that in this study, the exposure to AI was measured with the firm's occupational exposure, i.e. how likely the jobs of a company could be replaced by artificial intelligence technologies. However, this is clearly linked to AI investment in a form of potential for processes being automated by AI, which requires significant AI investments.

### **3.8 Compilation of findings**

Here we will compile the studies that examined abnormal returns and artificial intelligence. Note that many of these event studies utilized multiple event windows. However, the table below presents the longest event windows mentioned in the literature review for clarity and to present ideas of long-lasting AR effects. To see outcomes on all event windows, reference Chapter *Abnormal Returns of AI Technology* from the beginning onwards. Furthermore, studies covered that didn't specifically investigate abnormal returns are not visible in Table 5.

**Table 5.** Compilation of findings regarding abnormal returns of artificial intelligence.

<b>Study, (Year)</b>	<b>Method of Study</b>	<b>Sample</b>	<b>Period [Event Window]</b>	<b>Event window findings</b>	<b>Anomaly</b>	<b>Sector</b>
Ante & Saggu (2025)	Event Study, AI focus and AR	3395 NASDAQ companies	2011-2023 (3 months)	+20,97% CAR (Size Weighted)	Launch of ChatGPT	-
Lui et. al (2020)	Event Study, AI investment and AR	62 companies	2015-2019 [-1, +1]	- 4,94 % CAR	-	-
Pietrzak, (2025)	Event Study, ChatGPT announcements and AR	142 announcements	1 <sup>st</sup> of Jan- 31 <sup>st</sup> May, 2023 [-5, +5]	+2,7 % CAR for IT, No AR for others	-	IT, Finance, Industrial
Chou et. al (2026)	Event Study, AI AR vs. Control group AR	11 OpenAI announcements	2018-2024 [0, +5]	+1,67 % CAR for AI, Negative CAR for control group	ChatGPT Events 5, 7,8,9	AI
Malhotra et. al (2025)	Empirical panel-data study, risk-adjusted return models	180 ETFs	2000-2024	-0,05% CAR per month, insignificant	-0,41% CAR during 2020-2024	Data Centers
Xie (2024)	Event Study, AI Announcements	214 announcements	2020-2024 [0]	+1,1% AR	-	Platform Business
Ante & Demir (2023)	Event Study, AI token AR after the launch of ChatGPT 3.5	10 AI-themed tokens	30 <sup>th</sup> Nov. -14 <sup>th</sup> Dec. 2022. [0, +10]	+41% CAR	launch of ChatGPT	Crypto Currency
Hwang (2013)	Event Study, Pharmaceuticals AR during drug testing	138 AI announcements	2019-2023 [0]	Median CAR +0,8% for successful results	-	Medicine
Kurter & Bhatti, (2024)	Event Study, AR of AI-announcement of stock	138 AI announcements, FTSE100	2019-2023, [0]	0,11% insignificant AR on event day, Significant +1,6% AR for healthcare	Firm size and credit -factors found	-
Eisfeldt et. al, (2025)	Event Study, AR of firms with high occupational exposure to AI	5 907 publicly traded firms	15th Nov. 2022 – 31st March 2023, [0, +1]	+0,4% daily average AR for high AI-exposurefirms	-	-

## 4 Empirical Investigation on findings

This section continues the review of studies, but from an empirical standpoint, drawing on theory to understand the implications of scientific results. As was presented in Section *Theoretical Framework*, financial theory divides between theories of efficient and inefficient markets. Taking advantage of both viewpoints, we can have a comprehensive picture of the situation.

From Section *Abnormal Returns of AI Technology*, it becomes evident that Artificial Intelligence investment truly has potential to bring abnormal returns to firms, but some sectors tend to benefit more than others. Also, we can see several observations of significant changes during the sample period. Furthermore, some negative abnormal returns were found. We must also note that as this review progressed, we notified the intense motivation of firms to engage with artificial intelligence technologies. This strengthens the idea that firms truly see emerging potential in said technologies, but raises questions of potential AI washing that was briefly mentioned by Ante & Saggu (2025).

### 4.1 Efficient Markets Perspective

Empirical results indicate that investment and enterprise focus in artificial intelligence is positively correlated with abnormal returns. From the 10 scientific papers reviewed only one, by Lui et. al. (2020) showed significant negative abnormal returns of AI investment. In addition, the study by Malhotra et. al (2025) showed insignificant returns. Also, we must note that the sample size of the Lui et. al (2020) study is relatively small, with only 62 companies covered. This becomes evident when comparing the sample size to studies like one by Ante & Saggu (2025), which covered 3395 NASDAQ companies in the sample. Also, the analysis by Lui et. al. (2020) fails to consider the other market dynamic found, the ChatGPT impact. Of the eight remaining studies, that found positive AR, four (50 %) found relation to ChatGPT models going public. Even though not designed to handle only

LLM models, The literature suggests that this finding is important for understanding the topic.

From the basis of Efficient Market Theory (Fama, 1970) and the studies that show short term positive AR reactions of stock prices, we can conclude that artificial intelligence technologies do bring significant value to firms, with commercial LLM models standing out as the most value-bringing subset of AI. Also, observations suggest that sectors with advanced capabilities of IT adaptability were the strongest gainers. These sectors include platform enterprises, crypto currencies, AI as an industry, and possibly medicine. Surprisingly, finance industry couldn't be found among this list, despite generally viewed as IT oriented due to constant demands of digital currencies, transactions and markets (Ozili, 2023, p. 37). Also, Kurter & Bhatti, (2024) make the finding on firm size and credit -factors, which mean, that small firms with weaker credit score tend to be more associated with positive AR of AI than others. This could for example mean small technology firms, with high leverage and big bets in growing fields of IT like AI. By contrast, the firm size factor contradicts the findings by Ante and Saggu (2025), where size weighed index made significantly bigger abnormal returns than all the other indices which had more exposure to smaller companies. Thus, the firm size factor remains inconclusive.

Studies by Ante & Saggu (2025) and Eisfeldt et. al (2025) pose a critical challenge to the strongest forms of EMH. As seen in these studies, AI could not only bring short term reactions, but long, months lasting cumulative abnormal returns to firms. According to efficient market hypothesis, stocks should rapidly price the new, unsuspected information to the stocks, but in this case, the added value seems to be a constant phenomenon. This posits that markets regarding artificial intelligence might not be entirely efficient, as some levels of inefficiency was found.

## 4.2 Modeling Problem

We made another interesting finding when compiling the findings of literature: only studies that used Market Model (3) were able to find abnormal returns. The study by Lui et. al. (2020) used the CAPM, and the study by Malhotra et. al. (2025) used the Fama-French variation. We must note that Market Model was found to be clearly the most favoured model in event studies regarding expected returns, and this could be posited to be a product of its empirical nature, basing in realized market facts and not speculation. Regardless, this finding posits some suspicion about the impact of used model. However, if CAPM and Fama-French turn out to be weaker tools in calculating expected returns in an event study -based setting, then the findings about positive abnormal returns get once again more backing.

## 4.3 Inefficient Markets Perspective

As said, some evidence for market inefficiency was found in this thesis that challenges the EMH (Fama, 1970). We can find several examples of heuristic behavior (Kahneman & Tversky, 1974) to explain this continuous boom in AI stocks, resulting in long lasting abnormal returns.

**Table 6:** Examples of heuristic behaviour (Kahneman & Tversky, 1974).

<p><b>1. Representativeness</b></p>	<p>A mental shortcut where estimations are made by closeness to a stereotype instead of real statistical assessment.</p> <p>These stereotypes could be caused, for example, by specific news and media coverage, positive experiences with LLMs or linking artificial intelligence to previous success of technology companies.</p>

<p><b>2. Availability</b></p>	<p>Judging from the basis of how available the data regarding the concept is instead of how accurate the data regarding the concept is.</p> <p>Asymmetrical availability of data could be caused by the commercial incentive of AI companies to publish positive results, AI washing, or challenging nature of artificial intelligence theories.</p>
<p><b>3. Anchoring and Adjustment</b></p>	<p>Relying too heavily on initial piece of information (i.e. the anchor) and adjusting insufficiently to new information.</p> <p>The prior significant returns of AI could act as a significant behavioural anchor, driving investors to invest growing amounts into AI technologies and in some cases, treating it as a safe haven in the impending transformation of the job market.</p>

The heuristics highlighted in the table indicate that news coverage, personal experiences, narratives, and availability of information of artificial intelligence could contribute to systematic investor overreaction. This overreaction may take the form of increased demand and result in price pressure (Schleifer, 1986), which can lead to temporary abnormal returns among firms linked to artificial intelligence. In environments where liquidity is not sufficient, these demand shocks could cause surges in AI stock prices. Here, the theory of heuristics by Kahneman and Tversky links directly to demand shocks and price pressure theory by Schleifer.

We can also implement the Prospect Theory (1979) by Kahneman and Tversky to understand abnormal returns of AI. As the theory states, investors could have

asymmetrical orientations towards risks of securities. If AI stocks are seen as an asymmetrical opportunity, investors could overvalue small chances of big breakthroughs with said investments and thus create irrational price increases. Also, irrational avoidance of losses, which is a classic example from the theory, can cause investors to create irrational positive momentum to stocks which in turn leads to further increases in prices. Again, heuristic reactions to positive AI news could create asymmetrical perceptions of risk regarding AI technologies, leading to investors perceiving the upside potential of AI as unlimited. This perception could make artificial intelligence act as a safe haven for risk-averse investors.

We can find scientific literature that strengthens the argument about possible heuristic behavior of humans regarding artificial intelligence. A literature review by Kenesei et al. (2022) investigated the trust of people towards autonomous vehicles, comparing them to traditional commuting methods. They found that even though manufacturers and experts view autonomous vehicles as a much safer alternative to human-driven applications, they still face significant lack of trust as a major obstacle (Kenesei et al., 2022, p. 379). Also, the paper made another key finding: the amount of perceived trust to autonomous vehicles affected significantly the perceived risk (Kenesei et al., 2022, p. 391). This suggests that perceptions of risk are not based solely on factual evidence such as statistical data but are also strongly influenced by human perception and emotions. The perception of trust may be shaped by various factors, such as media coverage, personal experiences, and prior exposure to information technology, algorithms, or artificial intelligence.

Similar irrational and heuristic stances toward AI technologies were found in a study by Cheong et al. (2025). The results suggest that humans tend to undervalue capabilities of AI in specific areas, such as interpersonal skills (Cheong et al., 2025, p. 6). However, the paper also found that, for analytical tasks, people tend to favour AI's capabilities. Finally, Cheong et al. (2025) suggest that algorithm aversion and algorithm appreciation can coexist and that their influence varies depending on the nature of the task. In the

context of this thesis, the findings are relevant: humans not only tend to underestimate AI's capabilities but can also overvalue them in certain tasks.

From these studies we can point out that there is scientific backing to heuristic and inefficient behaviour of humans regarding artificial intelligence and its capabilities, and this could be also seen in financial markets. For example, the possibly idiosyncratic stance towards risk found in the study by Kenesei et. al. (2022) could also be present in investing and trading, and this could lead to suboptimal and inefficient choices in the market.

However, the findings here present mainly underestimation of AI technologies. On inefficient markets, abnormal stock returns for AI-related firms suggest that these technologies are more often overestimated than underestimated. Steyvers et al. (2025, p. 226) found, that participants on their study consistently overestimated the accuracy of LLM outputs. The findings were consistent with three different LLM models. Also, they found a length bias, which means that longer explanations from AI were linked to even higher human confidence levels, even though the longer explanations did not contain any additional information. Here we see significant irrational overestimation of LLM capabilities, that could reflect higher stock returns on inefficient markets. Furthermore, since these studies focus specifically on LLMs, they account for the overrepresentation of LLMs in abnormal returns relative to other AI technologies.

Finally, this section identified studies highlighting heuristic and sometimes irrational attitudes toward AI capabilities. Yet, the evidence points to both overestimation and underestimation occurring simultaneously, leaving the role of inefficient markets in explaining abnormal returns inconclusive.

## 5 Conclusion

This thesis examined how artificial intelligence (AI) adoption influences abnormal returns across the markets in the 21<sup>st</sup> century. The study was conducted as a literature review, and empirical research based on Efficient Market Hypothesis (EMH) and models to calculate expected and abnormal returns, such as Capital Asset Pricing Model, Fama-French Model and Market Model. Also, some theories regarding market inefficiency were highlighted for comparative value.

Two hypotheses,  $H_1$  and  $H_2$  were set, and they acted as the critical point of attention in the thesis. The first hypothesis stated that the adoption of technologies involving Artificial Intelligence indicate abnormal returns. On both, long and short event windows covered in the study, this hypothesis was strongly supported in the literature review, as eight out of ten studies resulted in significant abnormal returns. The hypothesis receives criticism only from one paper with opposing results, and one studying a specific sector and results indicating insignificance with abnormal returns. The second hypothesis stated that the prevalence of abnormal returns of AI investments varies significantly across industries. It received even stronger backing as the first hypothesis, with massive changes in abnormal returns in the 6 sector-specific studies.

To gain a perspective of a market participant, additional research questions,  $Q_1$  and  $Q_2$  were set. The first stated a question about the existence of notable changes found during the time period of study. The literature review gave a clear answer to the question, being the launch of public LLM-model ChatGPT 3.5. Out of 10 studies covered, five found linkages to market dynamics changing significantly at the point of this launch during November 30, 2022. From this point onwards, positive abnormal returns increased significantly, and the only study finding negative abnormal returns didn't cover this period. The impact of ChatGPT 3.5 was found to being so strong, that several AI indices constructed for the studies started a long lasting and systematic outperforming towards the overall market. This happened in multiple studies by different entities.

The second research question was posited to find answers to possible existence of any other additional factor found, that had impact on returns of AI. Again, answers were found to this question: companies with high capabilities of IT adaptation were found to being general gainers, and some evidence indicated in high credit-score diminishing possible returns. Also, some observations of a firm-size factor were made, but results of this remained inconclusive. Also, sectors like Finance and Data Centers could not be linked to abnormal returns, despite being at the center of AI adoption. However, coverage of these sectors was limited. Also, a modeling problem was found, where the only instances where CAPM or Fama-French was used, the studies couldn't find positive abnormal returns. Also, some indication towards market inefficiency, with reoccurring abnormal returns, was found, and thus, several ideas from the market inefficiency theories were deployed to find explanations for the phenomenon. Overall, both hypotheses could be accepted and answers to the research questions were delivered.

### **5.1 Limitations of the study**

Limitations of the study were also identified. First, the studies highlighted in the literature review implemented various models, notably the CAPM, Market Model and derivations of Fama-French model. As highlighted in Chapter *Theoretical Framework*, abnormal returns are constructed in differing ways from these models. This creates some limitation to comparing the results and was covered in Chapter *Modeling Problem*. Nonetheless, Market Model was found to be clearly the most favoured model by academics. Also, the variation in time frames employed across the studies may be regarded as a limitation when attempting to compare the findings. However, this also gave more perspective and from the point of view of the purpose of the study, it was crucial to know both, short and long timeframe indications of AI abnormal returns.

Furthermore, some studies could only be indirectly linked to abnormal returns, such as in Chapter *Technological Advancements in Medicine* and consequently, the conclusions drawn in the review may undermine the validity of the findings within the context of artificial intelligence returns.

Additionally, the novelty of commercial Artificial Intelligence could make it unpredictable, and prevalence or behaviour of abnormal returns could see significant changes during upcoming years and decades. Finally, it must be noted that studies investigating this phenomenon were found to be heavily concentrating in large language models, and this could have an impact on understanding artificial intelligence as a broader sense of technology.

## **5.2 Further discussion**

As the conclusion suggests, artificial intelligence has been a market-beating investment for investors for several years. However, this is only true when certain conditions apply. Because of the novelty and perceived potential of artificial intelligence, it is important to study these mechanics further. Empirical investigation of the study presents explanations regardless of the level of market efficiency. Further studies could continue pursuing these ideas.

As seen in the study, AI has also had significant changes in returns over the years, and the study could not find reasons why this could not happen again. Also, it must be noted that the future positive returns could intensify significantly. Hence, the study presents an interesting foundation and context for further academic studies to continue from.

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## **Appendices**

### **Appendix 1. Writing Notes**

This thesis used artificial intelligence tools in a limited and supportive method. The large language models used were OpenAI ChatGPT-4o and Google Gemini 1.5. These models were used to improve the clarity, grammar and logical flow of the thesis.

All decisions related to the academic work, research, conclusions and critical analysis were made solely by the author. The author is fully responsible for the work.