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ANALYSING COMPANIES THAT INVEST IN ARTIFICIAL INTELLIGENCE USING MARKOWITZ AND SHARPE

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ABSTRACT

This study explores the ever-evolving AI field with the ultimate goal of evaluating the risk-adjusted financial performance of AI-related companies in order to assess their overall attractiveness as investment opportunities as well as distinguish between those that can develop through private investment and those that require public support to remain competitive. Companies investing in AI were selected and grouped into broader sectors, and both Modern Portfolio Theory (MPT) and the Sharpe Ratio were applied to identify optimal portfolios that maximise risk-adjusted returns. The analysis outlines the optimal allocation of companies for each portfolio and examines their subregional and subsectoral distributions. Additionally, by assessing their annual performance using Sharpe Ratios, it provides insights into the influence of macroeconomic and geopolitical factors. Furthermore, benchmarking against major indices, namely the S&P 500 (US), CSI 300 (China), and DAX (Germany), helps determine whether the observed financial performance is truly robust and if the results obtained are unique to the AI sector or reflective of broader market trends. On the one hand, the findings indicate that the Software and Hardware sectors, along with the United States and East Asian countries such as China, Taiwan, South Korea and Japan, offer the best risk-return profiles. Consequently, given their lower risk-return attractiveness, it is recommended that authorities aid companies in the "Other" sector and Europe to strengthen their competitiveness. On the other hand, the analysis also indicates that the examined AI sectors demonstrate superior risk-adjusted financial performance compared to the benchmark indices, suggesting that investments in these sectors are indeed advantageous and worthwhile.

Keywords: Artificial Intelligence, sectors, indices, optimal portfolios, Markowitz, Maximum Sharpe Ratio.

RESUMEN

Este estudio explora el campo de la Inteligencia Artificial (IA) con el objetivo final de evaluar el desempeño financiero ajustado al riesgo de las empresas relacionadas con la IA para determinar su atractivo general como oportunidades de inversión y también distinguir entre aquellas que pueden desarrollarse mediante inversión privada y aquellas que requieren apoyo público para mantenerse competitivas. Se seleccionaron empresas que invierten en IA y se agruparon en sectores más amplios, aplicando tanto la Teoría Moderna de Portafolio (MPT) como el Ratio de Sharpe para identificar portafolios óptimos que maximizan los rendimientos ajustados al riesgo. El análisis detalla la asignación óptima de empresas para cada portafolio y examina sus distribuciones subregionales y subsectoriales. Además, al evaluar su desempeño anual mediante los Ratios de Sharpe, proporciona información sobre la influencia de factores macroeconómicos y geopolíticos. Asimismo, la comparación con índices principales, específicamente el S&P 500 (EE.UU.), CSI 300 (China) y DAX (Alemania), permite determinar si el desempeño financiero observado es verdaderamente sólido y también si los resultados obtenidos son exclusivos del sector de IA o reflejan tendencias más amplias del mercado. Por una parte, los resultados indican que los sectores de Software y Hardware, junto con Estados Unidos y países de Asia Oriental como China, Taiwán, Corea del Sur y Japón, ofrecen los mejores perfiles de riesgo-retorno. En consecuencia, debido a su menor atractivo en términos de riesgo y rendimiento, se recomienda que las autoridades brinden apoyo a las empresas del sector "Otros" y Europa para fortalecer su competitividad. Por otra parte, el análisis también señala que los sectores de IA examinados muestran un desempeño financiero ajustado al riesgo superior en comparación con los índices de referencia, lo que sugiere que las inversiones en estos sectores son realmente ventajosas y valiosas.

Palabras clave: Inteligencia Artificial, sectores, índices, portafolios óptimos, Markowitz, Máximo Ratio de Sharpe.

1 INTRODUCTION

In today's dynamic and increasingly complex investment landscape, investors are presented with an extensive spectrum of options. This overwhelming abundance of information oftentimes leads to confusion, leaving investors uncertain about their optimal course of action amidst the sheer volume of data available for financial analysis (Bernales et al., 2024). Navigating this complexity requires not only an advanced understanding of market fundamentals, but also the ability to discern meaningful signals from an ever-expanding sea of noise. Amidst this uncertainty, one trend has emerged with notable clarity: the accelerating growth and transformative potential of Artificial Intelligence (AI) (Haenlein & Kaplan, 2019). Companies at the forefront of AI innovation are not only reshaping entire industries but are also generating substantial economic value, thus positioning themselves as standout investment opportunities within an increasingly crowded marketplace.

Although research surrounding AI has expanded considerably in recent years, much of the existing literature does not specifically cover the aspects that this project aims to address. On the one hand, several studies have explored AI's application across various sectors, stressing its transformative potential in each context. Arinez et al. (2020) explore AI's integration in advanced manufacturing, emphasising its ability to drastically enhance operational efficiency as well as reduce costs through predictive maintenance. Amato et al. (2019) investigate AI's impact on the creative industries, particularly in reshaping artistic production and content creation. In the healthcare sector, Jiang et al. (2017) assess AI's role in advancing medical diagnostics and personalised treatment plans. On the other hand, an extensive body of research has analysed AI's integration within the financial domain, particularly in enhancing investment strategies and decision-making processes. Fatouros et al., 2024 explore the potential of ChatGPT in stock selection, demonstrating its ability to interpret financial narratives and outperform traditional models. Similarly, Romanko et al. (2023) examine the use of ChatGPT in investment portfolio construction, highlighting its assistance in enhancing informed financial decisions. Finally, Ferreira et al. (2021) provide an exhaustive review of AI methods used in stock market trading, highlighting their success in predicting market behaviour.

While these studies offer valuable insights into AI's potential, they often lack practical direction for investors and policymakers aiming to navigate the increasingly saturated and fast-changing AI market. There remains a significant gap in the literature regarding the identification and evaluation of companies within the AI ecosystem that represent the most promising investment opportunities.

This gap is essential given the accelerated pace of innovation, the emergence of new market entrants, and the difficulty in distinguishing between hype and long-term value (Ahmadirad; 2024).

Consequently, this project aims to achieve the following objectives: a) demystify the scope of AI by tracing its evolution from early conceptual foundations to its present-day applications and advancements as well as illustrate the reason behind selecting companies that invest in through an analysis of AI's total global economic impact and growth potential, while also considering ethical considerations that may potentially hinder its seemingly unstoppable growth; b) assess whether the financial performance of the selected AI-related sector is genuinely strong, and determine whether the outcomes are specific to the AI sector or indicative of wider market trends; c) identify the fields and regions that have offered the most favorable risk-return trade-offs over the past five years (2020–2024). This analysis aims to provide readers with actionable insights into AI-related trends, enabling them to tailor their portfolios according to their unique investment preferences and strategic objectives, and inform the relevant authorities about which market players are capable of self-driven development and which may require public support to foster growth and ensure competitiveness.

To accomplish this, both comprehensive qualitative attributes and essential quantitative financial data was compiled for 105 companies that heavily invest in AI using FactSet, a leading financial information provider, from January 1st, 2020, to September 30th, 2024. The selection of companies meeting the study's inclusion criteria was guided by two well-regarded AI-focused indices: the iSTOXX AI Global Artificial Intelligence 100 Index and the Morningstar Global Next Generation Artificial Intelligence Index. This dataset encompasses a heterogeneous array of firms differing in size, region, sector, and industry, thereby offering an understanding foundation for analysing investment trends within the AI market.

After categorising the selected companies into broader groups according to their sector, the analysis follows the principles of Modern Portfolio Theory (MPT), an established framework that optimises risk and return through diversification, developed by Harry Markowitz, alongside the Sharpe Ratio, a well-founded risk-adjusted performance measure that is used to compare different investment choices, introduced by William Sharpe, in order to identify the fields and regions that yield the strongest financial outcomes each year by focusing on the optimal portfolios that maximise the Sharpe Ratio. This methodological framework generates insights into AI-related investment patterns, highlighting where value is most effectively created across the ever-evolving AI market.

2 ARTIFICIAL INTELLIGENCE

2.1 AI CONCEPT AND SCOPE

AI is oftentimes misperceived as a recent innovation, with much of its origins and scope remaining widely misunderstood. This section will explore its historical evolution, shedding light on its evolution from early theoretical models to today's sophisticated, multi-modal systems.

The first concrete steps towards AI began with formal logic and computational theory in the 19th and early 20th centuries. Amongst the most renowned authorities, American mathematician George Boole introduced binary logic in his book "*The Mathematical Analysis of Logical*" in 1847, a framework for symbolic reasoning which enabled the representation of true and false values in mathematical form. Another noteworthy contributor was English mathematician Alan Turing, whose theoretical *Turing Machine* demonstrated the potential for machines to simulate human problem-solving. He later elaborated on this concept in his seminal paper "*Computing Machinery and Intelligence*", where he proposed the *Turing Test*, a tool used to determine whether machines could exhibit behaviour indistinguishable from humans (Haenlein & Kaplan, 2019; Mijwil, 2015).

The field of AI formally emerged in 1956 at the Dartmouth Conference, where John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon coined the term "*Artificial Intelligence*" and outlined their vision for machines capable of reasoning, problem-solving, and learning (Buchanan, 2005). This pioneering phase, commonly referred to as "*The AI Spring*", saw several pioneering programs demonstrated early success like the "General Problem Solver" (1957), an AI system designed to simulate human problem-solving behaviour, developed by Nobel-Prize winner Herbert Simon and scientists Cliff Shaw and Allen Newell, and "ELIZA" (1964-1966), an early natural language processing (NLP) chatbot developed by Joseph Weizenbaum (Haenlein & Kaplan, 2019; Mijwil, 2015).

Although AI showed early promise, it soon encountered significant hurdles. Limited computing power and difficulties in dealing with real-world complexity caused progress to stall, leading to what became known as the "First AI Winter" (Buchanan, 2005). Tensions around these challenges escalated in 1973, when Sir James Lighthill published an influential report criticising AI's slow progress and lack of real-world applications, leading many governments to significantly reduce or withdraw funding for AI research altogether (Buchanan, 2005). After this, AI made a brief comeback in the 1980s with expert systems, programs designed to mimic human decision-making, but both their high costs and lack of adaptability led to yet another funding decline, signaling the start of an era called "The Second AI Winter" (Haenlein & Kaplan, 2019).

A major turning point occurred in the late 1990s, as AI research gained renewed momentum, driven by significant advances in computational power, breakthroughs in algorithmic design, and the growing availability of Big Data (Haenlein & Kaplan, 2019). An important moment came in 1997, when IBM's Deep Blue defeated world chess champion Garry Kasparov, showcasing the power of AI in strategic decision-making (Buchanan, 2005; Mijwil, 2015).

As the 2000s began, AI applications steadily expanded into practical domains such as speech recognition, recommendation systems, and data mining, paving the way for many subsequent transformative developments (Haenlein & Kaplan, 2019; Mijwil, 2015). This period marked a shift from theoretical exploration to real-world integration, which was enabled through significant improvements in computational capacity, the availability of large-scale datasets, and evolving algorithmic frameworks (Mijwil, 2015). The 2010s witnessed an exponential acceleration in AI capabilities, largely driven by the resurgence of deep learning and neural networks, which facilitated substantial progress across various complex tasks (Haenlein & Kaplan, 2019). Among the most significant breakthroughs were advances in natural language processing, computer vision, and the emergence of Generative AI models, which collectively redefined the scope of machine intelligence and human-machine interaction (Buchanan, 2005).

Nowadays, the term AI refers to the constantly-evolving field of technology focused on developing computer systems capable of performing tasks traditionally associated with human intelligence (Jebara, 2002; Ng & Jordan, 2001;). These activities include learning, reasoning, problem-solving, perception, language processing, and decision-making, amongst others. AI achieves these capabilities through the integration of data-driven algorithms, machine learning, and computational processes designed to simulate as well as enhance cognitive functions (Jang et al., 2024).

AI's continuous advancements have resulted in the development of different classification frameworks to better understand its diverse scope. Amongst this myriad of groups, the most widely accepted one distinguishes AI into Generative and Discriminative AI.

On the one hand, Generative AI encompasses advanced systems that are capable of producing diverse forms of novel content including text, audio, images, and code (Banh et al., 2023; Jang et al., 2024). These systems leverage deep learning models to streamline tasks for users, providing tailor-made suggestions, variations, or solutions that mimic expert-level quality (Fernandez-Llorca et al., 2024). Consequently, Gen AI poses itself as an incredible transformative tool that provides well-rounded solutions that drive automation and augmentation across different domains worldwide (Banh et al., 2023).

On the other hand, Discriminative AI consists of advanced systems designed to classify, distinguish, or predict outcomes by learning the decision boundaries between different categories within data (Jebara, 2002; Ng & Jordan, 2001). Consequently, they are used in tasks like image recognition, fraud detection, and natural language processing (NLP), providing expert-level quality outcomes that enhance automation and decision-making across different industries worldwide (Jebara, 2002).

With the ongoing evolution of AI, the synergy between Generative and Discriminative AI is becoming increasingly pivotal, driving innovation worldwide (Jang et al., 2024). The rise of hybrid models that integrate both capabilities is revolutionising AI-powered solutions, reshaping the landscape of automation, decision-making, and problem-solving, thereby solidifying AI's status as one of the most transformative technological breakthroughs of the modern era (Banh et al., 2023).

2.2 AI MARKET DYNAMICS

AI stands amongst the most transformative breakthroughs in history and is expected to keep reshaping the world. The share of companies using AI in at least one business function jumped from 50% in 2020 to 78% by July 2024, underscoring AI's rapid integration into business operations (Singla et al., 2025). The most significant surge occurred between 2022 and 2024, which could be explained by the release of Generative Pre-trained Transformers (GPT) like Chat GPT by OpenAI, and Gemini by Google. Notably, ChatGPT became the fastest-growing consumer application in history, reportedly gaining 100 million active users within just two months of its its public release (Trautman et al., 2023), gaining traction amongst individuals and businesses alike.

AI's implementation has propelled extraordinary business outcomes, encompassing both revenue increases and cost reductions, resulting in companies that embrace AI obtaining competitive advantages, thereby increasing their likelihood of outperforming their competitors (Singla et al., 2025). This tendency highlights its importance when it comes to fostering operational excellence and securing long-term industry leadership in today's market landscape (Trautman et al., 2023).

Moreover, the total global economic impact of AI technologies is expected to range between $17.1 and $25.6 trillion by 2030 (McKinsey, 2023), highlighting its far-reaching economic potential and transformative power in the upcoming years. Reinforcing this outlook, another study anticipates that one in three companies across all markets is planning to invest at least $25 million in AI initiatives in 2025 (BCG, 2025). This widespread investment enthusiasm highlights a strong and sustained incentive to advance AI technologies, not only to broaden their functional capabilities but also to continuously enhance their overall performance and effectiveness (Bresnahan, 2023).

It is also worth noting that the compounding effect of digital and AI capabilities is rapidly widening the performance gap between industry leaders and laggards (Hall et al., 2024). Companies are now competing intensely to implement these solutions given that their early and effective adoption not only enhances existing competitive advantages, but also fosters the creation of new, difficult-to-replicate strengths (Hall et al., 2024). While large technology-driven companies often reap the greatest benefits, smaller or lagging companies still hold potential to excel by embedding digital and AI technologies within their core competencies, thus catalysing transformative growth and ultimately positioning themselves securely for the future (Bresnahan 2023; Trautman et al., 2023).

In other words, AI is reshaping countless different industries, revolutionising the way organisations operate across their entire value chains. For instance, regarding the entertainment industry, AI-powered recommendation algorithms are revolutionising content consumption by analysing user behaviour and preferences to accurately suggest hyper-personalised content, thereby boosting both user engagement and satisfaction (Amato et al., 2019). When it comes to the healthcare industry, AI-powered wearable devices continuously monitor vital signs and detect anomalies, enabling early interventions and proactive care, while AI-powered assistant robots are increasingly supporting critical functions, from assisting in the performance of medical procedures to aiding in the development of new treatments, collectively enhancing the overall quality of patient care (Jiang et al., 2017). Meanwhile, the manufacturing industry is also experiencing drastic changes, with AI-driven predictive maintenance systems being used to anticipate equipment failures, thereby enabling timely interventions that reduce downtime, extend equipment lifespan, and lower maintenance costs while also boosting productivity (Arinez et al., 2020).

2.3 AI ETHICAL CONSIDERATIONS

However, despite its seemingly benign promise, AI raises pressing concerns, particularly in areas including privacy, data protection, misinformation, copyright infringement, and societal inequality (Bevilacqua et al., 2024). In today's investment landscape, financial performance is no longer the sole driver of decision-making, as investors increasingly prioritise alignment with environmental, social, and governance (ESG) values. Resulting from this, companies entangled in AI-related ethical controversies face reputational risks, eroded stakeholder trust, and limited access to capital (Trautman et al., 2023). Consequently, if unaddressed, these concerns could deter investment, hinder projected growth, or lead to even broader negative consequences, especially if AI's continuous advancements keep outpacing the ability of policymakers to assimilate and regulate them within comprehensive legal and regulatory frameworks (Trautman et al., 2023).

AI possesses the remarkable capability to generate diverse forms of novel content including text, audio, images, and code, thereby providing customised suggestions, variations, or solutions that mirror expert-level results (Fernandez-Llorca et al., 2024). Nevertheless, as these systems become increasingly sophisticated, their ability to generate hyper-realistic deepfakes, manipulate digital content, and automate disinformation campaigns undermines the integrity of information, eroding public trust and making it increasingly difficult to distinguish fact from fiction (Banh et al., 2023).

Moreover, AI's reliance on datasets, often scraped indiscriminately from publicly available sources including websites, books, images, music, and social media, raises major copyright and intellectual property concerns (Elkin-Koren et al., 2023). Since these models are frequently trained on vast datasets containing copyrighted materials, they sometimes inevitably replicate or mimic protected content without proper attribution or compensation. This practice has sparked debates over fair use and content ownership, raising complex legal and ethical questions (Elkin-Koren et al., 2023).

Additionally, concerns about algorithmic bias and social inequality remain deeply consequential. Since AI models are trained on historical data, they risk perpetuating and amplifying existing societal biases, which can lead to systematically unfair or discriminatory outcomes, particularly in high-stakes domains such as hiring, lending, and law enforcement (Jebara, 2002; Ng & Jordan, 2001). These patterns not only reflect past prejudices but may also institutionalise them under the guise of objectivity, raising urgent ethical and accountability challenges (Elkin-Koren et al., 2023).

Last but not least, AI is poised to significantly transform the workforce. Experts estimate that by 2045, half of today's work activities could be automated, a full decade earlier than previously anticipated (Hall et al., 2024). This accelerated shift raises the prospect of widespread job displacement, large-scale workforce restructuring, and the urgent need for reskilling and policy adaptation to mitigate economic and social disruption.

3 THEORETICAL FRAMEWORK

This analysis begins with Harry Markowitz's Mean-Variance framework, a foundational concept of Modern Portfolio Theory (MPT), which provides a systematic approach to constructing efficient portfolios by optimising the trade-off between risk and return (Fabozzi et al., 2002; Markowitz, 1952). This model identifies the efficient frontier, which represents the set of portfolios that offer the highest possible return for a given level of risk or the lowest possible risk for a given level of return (Markowitz, 1952). However, while Markowitz's framework is instrumental in outlining theoretically optimal investment combinations, it fails to indicate the most compelling one (Fabozzi et al., 2002). To address this limitation, the Sharpe Ratio is used as a complementary evaluative tool since it measures the excess return obtained per unit of risk undertaken, thereby facilitating direct, risk-adjusted comparisons across different portfolios (Bodie et al., 2013; Sharpe, 1994).

Several other studies have also based their methodological approach on constructing optimal portfolios using the Mean-Variance framework and subsequently selecting those that maximise the Sharpe Ratio in order to identify the most favorable risk-return profiles. For instance, Pedersen et al. (2021) adapt the mean-variance framework to responsible investing by introducing the ESG-efficient frontier, enabling investors to optimise portfolios that balance risk-adjusted returns with sustainability goals. Romanko et al. (2023) leverage Chat GPT to support portfolio selection, combining Mean-Variance analysis with the Sharpe Ratio to construct portfolios tailored to investor objectives. Likewise, Qu & Zhang (2023) explore the application of both maximum Sharpe Ratio and minimum variance strategies across different industry sectors, aiming to identify sector-specific portfolio configurations that deliver optimal risk-adjusted returns.

3.1 HARRY MARKOWITZ - MEAN VARIANCE ANALYSIS

Developed in 1952 by Novel Laureate Harry Markowitz, Modern Portfolio Theory (MPT) represented an absolutely groundbreaking framework for constructing efficient, well-diversified portfolios that maximise returns for given levels of risk or minimise risk for given levels of return (Markowitz, 1952). Initially published in "The Journal of Finance", its renowned article "Portfolio Selection" originally generated little interest amongst the finance community. However, over time, his revolutionary work became widely accepted, leading to continuous improvements in financial models based on its principles (Fabozzi et al., 2002).

At that time, many investors and analysts relied heavily on intuition and subjective judgment rather than rigorous quantitative models. Markowitz's unique emphasis on mathematical formulations, which involved complex statistical analyses to assess correlations and optimise returns, challenged conventional investment practices (Markowitz, 1952). Many practitioners were unaccustomed to the notion of evaluating investments through the lens of risk-return trade-offs, making it obstructive for Markowitz's ideas to penetrate the prevailing mindset, resulting in his ideas being dismissed and ignored by the investment community (Fabozzi et al., 2002). Notwithstanding, it was only in the subsequent decades, as financial markets became increasingly complex, that the pressing need for robust analytical frameworks became unmistakably clear (Fabozzi et al., 2002). Amidst this shifting landscape, Modern Portfolio Theory (MPT) gradually gained momentum, eventually earning its rightful recognition as a fundamental pillar of contemporary finance, shaping investment strategies and practices alike (Fabozzi et al., 2002).

Mean-Variance analysis is fundamentally rooted in the principle of portfolio diversification, which enables meaningful risk mitigation. While strategic asset allocation can substantially reduce portfolio risk, it cannot eliminate it entirely due to overarching factors that drive persistent correlations among assets (Markowitz, 1952). Despite this limitation, financial authorities actively advocate for maintaining well-diversified portfolios, which implies allocating capital across different assets with low or negative correlations in order to obtain favourable risk-return trade-offs as well as consistent financial outcomes (Fabozzi, et al., 2002).

This approach requires the simultaneous resolution of two optimisation problems: maximising returns and minimising risk. This enables the calculation of the maximum return for each level of risk and, conversely, the minimum risk for each level of return, thereby tracing the efficient frontier (Fabozzi, et al., 2002; Markowitz, 1952). In this context, the efficient frontier serves as a fundamental graphical representation of optimal portfolios, aiding investors in selecting portfolio allocations that align with their unique investment objectives (Markowitz, 1952; Shape 1994).

The portfolios are calculated by simultaneously solving the following equations:

$$Maximize\ E[R_p] = \sum_{i=1}^{N} w_i\, E[R_i]$$

$$Minimize\ \sigma_p^2 = \sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} w_i w_j \sigma_{i,j}$$

Where:

- σ_p^2: Portfolio's variance
- σ_i^2: Each asset's variance
- σ_{ij}: Covariance between the returns of i and j
- w_i: Weight assigned to each asset
- E (R_i): Expected return for each asset
- E (R_p): Expected portfolio return
- N: Number of assets in the portfolio

Subject to:

$$w_i \geq 0, \quad \forall i \in \{1, 2, \ldots, n\}$$

$$\sum_{i=1}^{n} w_i = 1$$

In Markowitz's Mean-Variance framework, portfolio construction may include constraints such as (1) the prohibition of short-selling, by restricting asset weights to non-negative values, ensuring that investors cannot take leveraged positions or bet against specific assets, and (2) the requirement that the sum of all weights equals one, ensuring that the portfolio remains fully invested within its allocated capital (Markowitz, 1952).

3.2 WILLIAM SHARPE - THE SHARPE RATIO

Named after its creator, William Sharpe, the Sharpe Ratio is a widely recognised financial metric that quantifies the excess return earned per unit of risk taken (Sharpe, 1966). Nearly three decades later, Sharpe refined the ratio to account for time-varying risk-free rates, resulting in the standardised definition that remains prevalent in modern financial analysis (Sharpe, 1994). This foundational measure of risk-adjusted performance defines excess return as the difference between a portfolio's return and the risk-free rate, typically represented by the yield on government securities with negligible default risk. By incorporating both return and volatility, the Sharpe Ratio provides a robust tool for evaluating financial performance and facilitates comparisons across different investment choices (Sharpe, 1994).

The Sharpe Ratio is mathematically expressed as follows:

$$Sharpe\ Ratio\ (SR) = \frac{R(p) - Rf}{\sigma(p)}$$

Where:

- SR: Sharpe Ratio
- Rp: Portfolio return
- Rf: Risk-free rate
- σp: Portfolio risk

The Sharpe Ratio offers investors critical insights into the risk-adjusted performance of their portfolios, allowing them to distinguish between overperforming and underperforming investment decisions. Its combination of conceptual simplicity and analytical power makes it an indispensable tool for evaluating financial performance, uncovering investment opportunities, and guiding portfolio optimisation (Bodie et al., 2013). Ultimately, a higher Sharpe Ratio reflects a more favorable balance between risk and return, which is why it has been chosen as the primary metric for comparing portfolio alternatives.

4 EMPIRICAL ANALYSIS

4.1 DATABASE

In order to identify companies that actively invest in AI, two prominent AI-focused indices have been selected: the iSTOXX AI Global Artificial Intelligence 100 Index and the Morningstar Global Next Generation Artificial Intelligence Index. Grounded in the constituent selections of these indices, comprehensive qualitative attributes alongside quantitative financial data were gathered using FactSet, a leading provider of financial analytics and market data.

Data for these companies has been collected from their inception until September 30th, 2024, which marks the cutoff date. To ensure analytical precision, this dataset has been refined to cover the period from January 1st, 2020, to September 30th, 2024, and companies with gaps or inconsistencies in their financial records, particularly when misaligned with the study's selected timeframe, were excluded. Following these adjustments, the resulting dataset contains 105 AI-focused companies that span different sizes, geographies, industries, and sectors, thereby offering an insightful framework for analysing AI investment trends.

This timeframe was chosen since it encompasses key events that significantly impacted the AI landscape. Notably, the accelerated digital transformation that followed the COVID-19 pandemic laid the foundation for groundbreaking advancements, including the emergence of AI-powered tools such as ChatGPT and Gemini, which expanded AI's role across both professional and everyday domains (Maslej et al., 2025). Additionally, the Russia-Ukraine war triggered widespread global disruption, interrupting supply chains and destabilising key economic sectors (Gehrmann et al., 2025). Concurrently, this period also covers pivotal regulatory developments, most notably the European Union's approval of the AI Act, the world's first comprehensive regulatory AI framework, which introduced new challenges as well as marked an important shift in both governance and compliance within the industry (Fernández-Llorca et al., 2024).

Furthermore, some indices, namely the S&P 500 (US), CSI 300 (China), and DAX (Germany), have been analysed as they serve as financial performance benchmarks. By comparing the performance of AI-related sectors to these broader indices, it becomes possible to determine whether the observed sectoral gains are truly exceptional or simply reflective of general market trends.

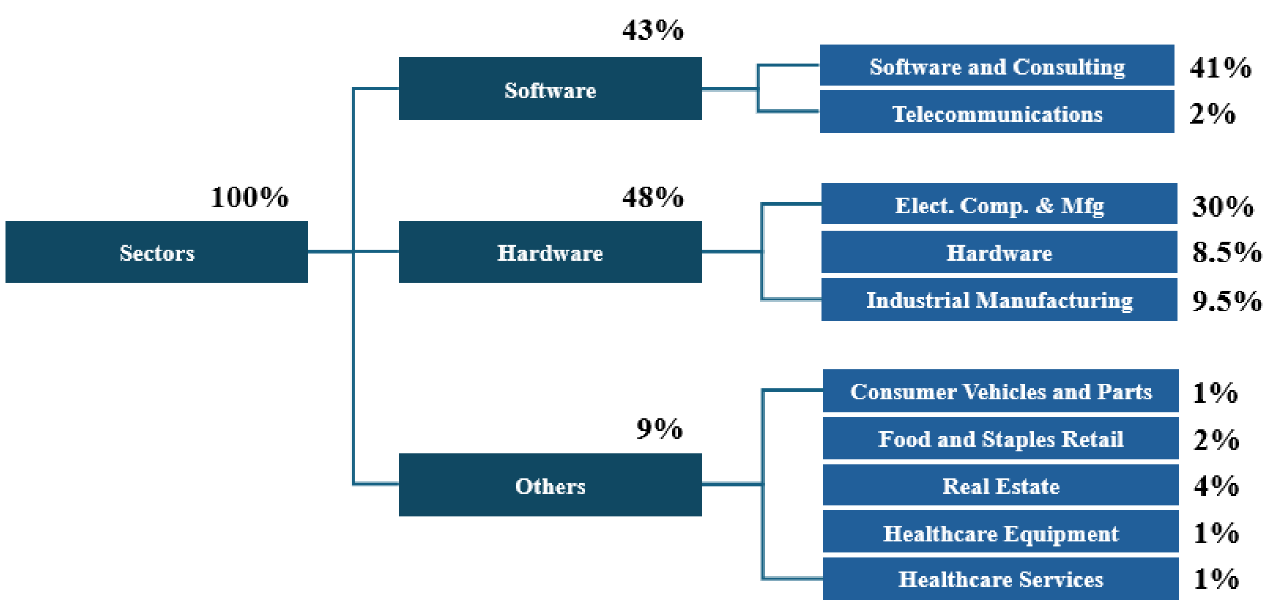
Lastly, regarding risk-free rates, daily 10-year Treasury bond yields were collected for the period spanning January 1st, 2020, to September 30th, 2024, ensuring alignment with the timeframe used for stock prices. To account for regional differences, countries with the highest representation or symbolic presence within their respective geographic regions were selected as benchmarks. Consequently, the U.S. 10-year Treasury bond yield serves as the risk-free rate for the companies included in the "America" region, China represents the "Asia-Pacific" region, and Germany symbolises the "Europe" region.

4.2 DESCRIPTIVE ANALYSIS

The selected companies are defined by seven key attributes: company name, founding year, stock symbol, stock exchange, geography, sector, and industry. Among these, the variables "geography" and "sector" are particularly valuable for analysis. On one hand, they act as powerful filters for selecting companies that align with unique investor goals, market trends, regional growth, and sector opportunities, thereby supporting optimal investment decision-making. On the other hand, they offer insights into company performance across regions and sectors, helping authorities identify areas needing support to remain competitive.

4.2.1 DISTRIBUTION BY SECTOR

Figure 1: Distribution of companies by sector

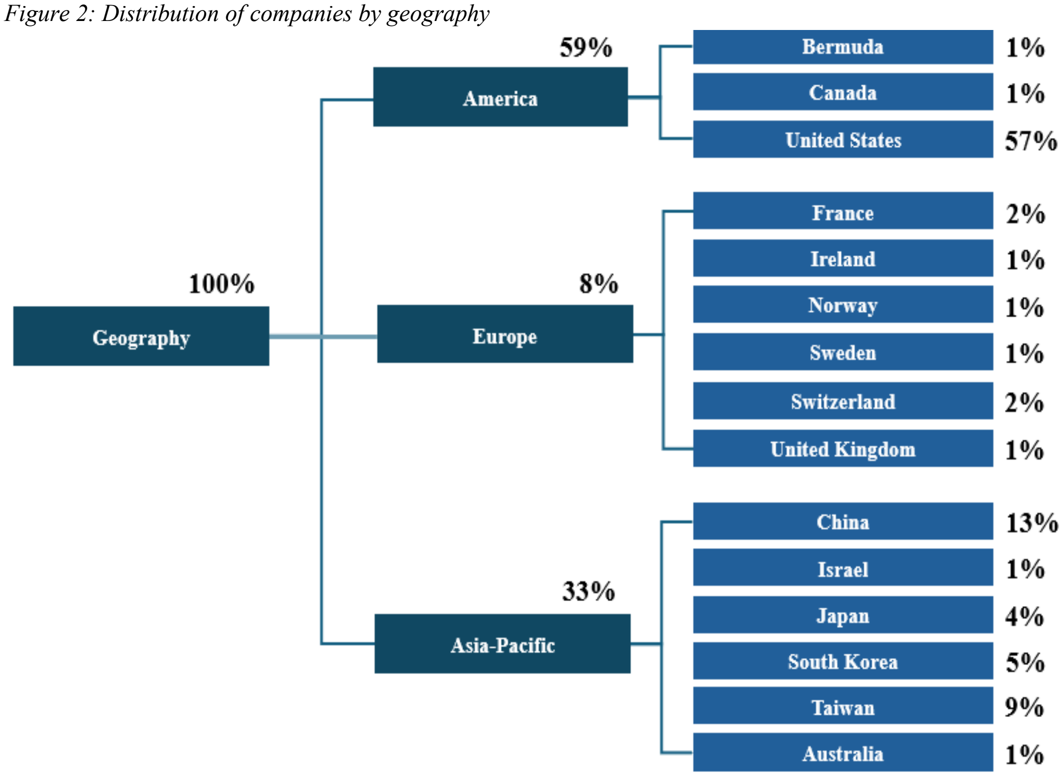


Source: Own elaboration

Regarding sectoral distribution, the analysed companies are organised across 10 different sectors, which have been grouped into 3 overarching categories: Software, Hardware, and 'Others'. The distribution reveals a significant concentration in the Hardware category, which includes 51 companies, driven primarily by Electronic Components and Manufacturing (32), with additional representation from Industrial Manufacturing (10) and Hardware (9). The Software group follows with 45 companies, predominantly composed of firms in Software and Consulting (43) and a smaller share in Telecommunications (2). The remaining 9 companies fall under the 'Others' category, covering sectors such as Real Estate (4), Food and Staples Retail (2), Healthcare Equipment (1), Healthcare Services (1), and Consumer Vehicles and Parts (1). This analysis highlights the dual nature of AI investment, driven by an iterative and synergistic cycle of innovation in both software and hardware, where software advancements continuously enhance AI's potential, while hardware breakthroughs provide the computational power necessary to fully harness those capabilities. Furthermore, the 'Others' category underscores the broad applicability of AI across diverse sectors beyond traditional tech.

4.2.2 DISTRIBUTION BY GEOGRAPHY

Figure 2: Distribution of companies by geography

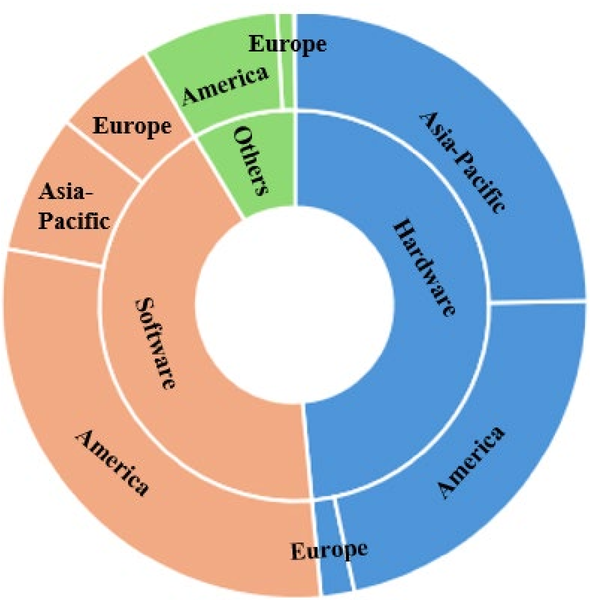


Source: Own elaboration

Regarding geographical distribution, the companies are based across 15 different countries, and have been strategically consolidated into 3 broader regions: America, Europe, and Asia-Pacific. This classification facilitates clearer analysis of location-based trends and enables more geographically targeted portfolio construction, considering regional economic conditions, policy environments, and market maturity levels. The distribution reveals a pronounced concentration in America, with 62 companies, the vast majority of which are based in the United States (60), alongside Canada (1) and Bermuda (1). Asia-Pacific follows with 35 companies, represented by China (14), Taiwan (10), South Korea (5), Japan (4), Israel (1), and Australia (1). Meanwhile, Europe has the smallest share, with 8 companies, spread across France (2), Switzerland (2), Ireland (1), Norway (1), Sweden (1), and the United Kingdom (1). This breakdown underscores the intensifying global competition in the AI investment landscape, as the historically dominant American tech sector now contends with the rising influence of East Asian players amidst an escalating race for technological leadership.

4.2.3 DISTRIBUTION BY SECTOR AND GEOGRAPHY

Figure 3: Distribution of companies by geography and sector



Source: Own elaboration

An intersectional analysis of sectoral distribution across regions reveals insightful patterns. This combined classification provides an enhanced understanding of the global distribution of sectoral strengths, offering valuable insights for region-specific portfolio construction and the formulation of thematic investment strategies. Firstly, Hardware companies are relatively evenly distributed between America (23) and Asia-Pacific (26), with minimal representation in Europe (2). Secondly, in the Software sector, the concentration is more pronounced, with America demonstrating clear dominance (31), significantly outnumbering both Asia-Pacific (8) and Europe (6). Finally, the 'Others' category, is exclusively represented by America (8) and Asia-Pacific (1). Given these findings, it can be hypothesised that the geographic disparity in sectoral distribution reflects global trends in AI development, whereby the United States continues to dominate software and cross-sector applications, while East Asia emerges as an aggressive competitor in hardware.

Table 1: Overview of the selected companies

Constituent Name	Founded	Symbol	Stock Exchange	Geography	Sector	Industry
Accenture	2009	ACN-US	NYSE	Ireland	Software and Consulting	Information Technology Consulting
Adobe	1982	ADBE-US	NASDAQ	United States	Software and Consulting	Specialized Design and Engineering Software
Advanced Micro Devices	1969	AMD-US	NASDAQ	United States	Electronic Components and Manufacturing	Multimedia Semiconductors
Amazon	1994	AMZN-US	NASDAQ	United States	Food and Staples Retail	Internet Department Stores
Ansys	1970	ANSS-US	NASDAQ	United States	Software and Consulting	Computer Aided Design Software
Autodesk	1982	ADSK-US	NASDAQ	United States	Software and Consulting	Computer Aided Design Software
Cognizant Technology Solutions	1988	CTSH-US	NASDAQ	United States	Software and Consulting	Information Technology Consulting
Alphabet (Google)	2015	GOOGL-US	NASDAQ	United States	Software and Consulting	Web-Related Content Providers
IBM	1911	IBM-US	NYSE	United States	Software and Consulting	Information Technology Consulting
Intel	1968	INTC-US	NASDAQ	United States	Electronic Components and Manufacturing	Microprocessor Semiconductors
Marvell Technology	1995	MRVL-US	NASDAQ	United States	Electronic Components and Manufacturing	Microprocessor Semiconductors
Microsoft	1975	MSFT-US	NASDAQ	United States	Software and Consulting	General and Mixed-Type Software
NVIDIA	1993	NVDA-US	NASDAQ	United States	Electronic Components and Manufacturing	Multimedia Semiconductors
Oracle	1977	ORCL-US	NYSE	United States	Software and Consulting	Diversified Hosting Services
PTC	1985	PTC-US	NASDAQ	United States	Industrial Manufacturing	Manufacturing Ind United Statestry Software
QUALCOMM	1985	QCOM-US	NASDAQ	United States	Electronic Components and Manufacturing	Communications Semiconductors
Salesforce	1999	CRM-US	NYSE	United States	Software and Consulting	Customer Relationship Management Software
CGI	1976	GIB.A-CA	Toronto	Canada	Software and Consulting	Design, Integration and Implementation Consulting
Super Micro Computer	1993	SMCI-US	NASDAQ	United States	Hardware	Server Computer Systems
Genpact	1997	G-US	NYSE	Bermuda	Software and Consulting	Information Technology Consulting
Capgemini	1984	CAP-FR	Euronext Paris	France	Software and Consulting	Information Technology Consulting
Dassault Systemes	1981	DSY-FR	Euronext Paris	France	Software and Consulting	Computer Aided Design Software
Taiwan Semiconductor Manufacturing	1987	2330-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Semiconductor Foundry Services
SK Hynix	1949	000660-KR	Korea	South Korea	Electronic Components and Manufacturing	Volatile Memory Semiconductors
NAVER	1999	035420-KR	Korea	South Korea	Software and Consulting	Web-Related Content Providers
Broadcom	1961	AVGO-US	NASDAQ	United States	Electronic Components and Manufacturing	RF Analog and Mixed Signal Semiconductors
Fortinet	2000	FTNT-US	NASDAQ	United States	Software and Consulting	Network Infrastructure Software
Alchip Technologies	2003	3661-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Other Programmable Logic and ASIC Semiconductors
Meta (Facebook)	2004	META	NASDAQ	United States	Software and Consulting	Consumer Content Providers
ServiceNow	2004	NOW-US	NYSE	United States	Software and Consulting	General Enterprise Management Software
Palo Alto Networks	2005	PANW-US	NASDAQ	United States	Hardware	Network Infrastructure Software
Arista Networks	2004	ANET-US	NYSE	United States	Hardware	Carrier Core (Backbone) Equipment
Okta	2009	OKTA-US	NASDAQ	United States	Software and Consulting	Network Infrastructure Software
MongoDB	2007	MDB-US	NASDAQ	United States	Software and Consulting	Data Storage Infrastructure Software
Zscaler	2007	ZS-US	NASDAQ	United States	Software and Consulting	Network Infrastructure Software
Crowdstrike Holdings	2011	CRWD-US	NASDAQ	United States	Software and Consulting	Network Infrastructure Software
Cloudflare	2009	NET-US	NYSE	United States	Software and Consulting	Internet Support Services

Source: Own elaboration

Table 1: Overview of the selected companies

Constituent Name	Founded	Symbol	Stock Exchange	Geography	Sector	Industry
BILL Holdings	2006	BILL-US	NYSE	United States	Software and Consulting	Enterprise Resource Planning Software
Tencent	1998	700-HK	Hong Kong	China	Software and Consulting	Multi-Type Home and Office Software
Alibaba	1999	9988-HK	Hong Kong	China	Food and Staples Retail	Internet Department Stores
Vertiv	1946	VRT-US	NYSE	United States	Industrial Manufacturing	General IndUnited Statestrial Electrical Products
Advantest	1946	6857-JP	Tokyo	Japan	Electronic Components and Manufacturing	Semiconductor Process Control Equipment
EPAM Systems	1993	EPAM-US	NYSE	United States	Software and Consulting	Software Design and Engineering Consulting
Onto Innovation	1940	ONTO-US	NYSE	United States	Electronic Components and Manufacturing	Semiconductor Process Control Equipment
Amkor Technology	1968	AMKR-US	NASDAQ	United States	Electronic Components and Manufacturing	Semiconductor Packaging and Testing Services
Camtek	1987	CAMT-US	NASDAQ	Israel	Electronic Components and Manufacturing	Semiconductor Process Control Equipment
MicroStrategy	1989	MSTR-US	NASDAQ	United States	Software and Consulting	Business Intelligence Software
Lattice Semiconductor	1983	LSCC-US	NASDAQ	United States	Electronic Components and Manufacturing	Programmable Logic Device Semiconductors
Micron Technology	1978	MU-US	NASDAQ	United States	Electronic Components and Manufacturing	Volatile Memory Semiconductors
Pinterest	2008	PINS-US	NYSE	United States	Software and Consulting	Consumer Content Providers
China Tower	2014	788-HK	Hong Kong	China	Telecommunications	Wireless Infrastructure Services
Hexagon AB	1975	HEXA.B-SE	OMX Nordic Stockholm	Sweden	Industrial Manufacturing	Monitoring and Control Sensor/Instrument Products
Cogent Communications Holdings	1999	CCOI-US	NASDAQ	United States	Telecommunications	Telecommunications Carrier Services
VIA Technologies	1992	2388-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Microprocessor Semiconductors
Intuitive Surgical	1995	ISRG-US	NASDAQ	United States	Healthcare Equipment	Surgical Devices
DocUnited Statesign	2003	DOCU-US	NASDAQ	United States	Software and Consulting	Content Management Software
SBA Communications	1989	SBAC-US	NASDAQ	United States	Real Estate	Equity REITs
American Tower	1995	AMT-US	NYSE	United States	Real Estate	Equity REITs
Yokogawa Electric	1915	6841-JP	Tokyo	Japan	Industrial Manufacturing	General Factory Automation Product Manufacturing
RadNet	1980	RDNT-US	NASDAQ	United States	Healthcare Services	Other Ambulatory and Outpatient Diagnostic Care
Equinix	1998	EQIX-US	NASDAQ	United States	Real Estate	Equity REITs
Digital Realty TrUnited Statest	2004	DLR-US	NYSE	United States	Real Estate	Equity REITs
Seagate Technology	1978	STX-US	NASDAQ	United States	Hardware	Data Storage Drives and Peripherals
Western Digital	1970	WDC-US	NASDAQ	United States	Hardware	Data Storage Drives and Peripherals
NetApp	1992	NTAP-US	NASDAQ	United States	Hardware	Information and Disk Storage Systems
Pure Storage	2009	PSTG-US	NYSE	United States	Hardware	Data Storage Drives and Peripherals
Nextdc	2010	NXT-AU	ASX	Australia	Software and Consulting	Colocation and Data Center Services
Cognex	1981	CGNX-US	NASDAQ	United States	Industrial Manufacturing	Machine Vision and Quality Control Manufacturing
Elastic	2012	ESTC-US	NYSE	United States	Software and Consulting	Business Intelligence Software
Box	2005	BOX-US	NYSE	United States	Software and Consulting	Content Management Software
Teradata	1979	TDC-US	NYSE	United States	Software and Consulting	Business Intelligence Software
Ambarella	2004	AMBA-US	NASDAQ	United States	Electronic Components and Manufacturing	Multimedia Semiconductors
Clarivate	1864	CLVT-US	NYSE	United Kingdom	Software and Consulting	Business Intelligence Software
Kingdee International Software	1993	268-HK	Hong Kong	China	Software and Consulting	Enterprise Resource Planning Software

Source: Own elaboration

Table 1: Overview of the selected companies

Constituent Name	Founded	Symbol	Stock Exchange	Geography	Sector	Industry
Faraday Tech	1993	3035-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Other Programmable Logic and ASIC Semiconductors
COMET Holding AG	1948	COTN-CH	SIX Swiss	Switzerland	Industrial Manufacturing	Machine Vision and Quality Control Manufacturing
GDS	1952	GD-US	NYSE	United States	Industrial Manufacturing	Diversified Aerospace and Defense Manufacturing
Macronix	1989	2337-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Nonvolatile Memory Semiconductors
Asmedia Technology	2004	5269-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Communications Semiconductors
SoftwareOne	2000	SWON-CH	SIX Swiss	Switzerland	Software and Consulting	Design, Integration and Implementation Consulting
RAK United States	2000	3923-JP	Tokyo	Japan	Software and Consulting	General Enterprise Management Software
Fastly	2011	FSLY-US	NYSE	United States	Software and Consulting	Colocation and Data Center Services
Airoha Technology	2001	6526-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Other Programmable Logic and ASIC Semiconductors
Transcend Info	1988	2451-TW	Taiwan	Taiwan	Hardware	Data Storage Media
EMST	1998	3006-TW	Taiwan	Taiwan	Electronic Components and Manufacturing	Other Memory Semiconductors
Crayon	2011	CRAYN-NO	Oslo	Norway	Software and Consulting	Information Technology Consulting
MaxLinear	2003	MXL-US	NASDAQ	United States	Electronic Components and Manufacturing	Other Specialized Semiconductors
Montage Technology	2004	688008-CN	Shanghai	China	Electronic Components and Manufacturing	Other Memory Semiconductors
CMC Magnetics	1978	2323-TW	Taiwan	Taiwan	Hardware	Data Storage Media
SAKURA Internet	1996	3778-JP	Tokyo	Japan	Software and Consulting	Managed Hosting Services
Bandwidth	2000	BAND-US	NASDAQ	United States	Software and Consulting	Communications Infrastructure Software
Jeju Semiconductor	2000	080220-KR	Korea	South Korea	Electronic Components and Manufacturing	Nonvolatile Memory Semiconductors
Giga Device Semiconductor	2005	603986-CN	Shanghai	China	Electronic Components and Manufacturing	Nonvolatile Memory Semiconductors
Domo	2010	DOMO-US	NASDAQ	United States	Software and Consulting	Business Intelligence Software
Unigroup Guoxin Microelectronics	2001	002049-CN	Shenzhen	China	Electronic Components and Manufacturing	Other Programmable Logic and ASIC Semiconductors
Ingenic Semiconductor	2005	300223-CN	Shenzhen	China	Electronic Components and Manufacturing	Microprocessor Semiconductors
Amlogic	2003	688099-CN	Shanghai	China	Electronic Components and Manufacturing	Multimedia Semiconductors
HyVISION System	2010	126700-KR	Korea	South Korea	Industrial Manufacturing	Machine Vision and Quality Control Manufacturing
ADTechnology	2002	200710-KR	Korea	South Korea	Electronic Components and Manufacturing	Other Programmable Logic and ASIC Semiconductors
Wangsu Science & Technology	2000	300017-CN	Shenzhen	China	Software and Consulting	Software and Consulting
Allwinner Technology	2007	300458-CN	Shenzhen	China	Electronic Components and Manufacturing	Microprocessor Semiconductors
Wuhan Jingce Electronic	2006	300567-CN	Shenzhen	China	Industrial Manufacturing	Machine Vision and Quality Control Manufacturing
Hunan Goke Microelectronics	2008	300672-CN	Shenzhen	China	Electronic Components and Manufacturing	Multimedia Semiconductors
Hefei Meyer Optoelectronic Technology	2000	002690-CN	Shenzhen	China	Industrial Manufacturing	Machine Vision and Quality Control Manufacturing
Tesla	2003	TSLA-US	NASDAQ	United States	Consumer Vehicles and Parts	Car Manufacturers

Source: Own elaboration

4.3 PYTHON ANALYSIS

The purpose of this section is to explain the methodology used to calculate the Portfolios that maximise the Sharpe Ratio using Python code. This includes an explanation of the calculations performed, the formulas applied, and the rationale behind their selection. Python was chosen as the primary tool for this analysis due to its flexibility, computational efficiency, and wide range of well-supported libraries tailored for quantitative finance. Compared to spreadsheet-based tools or other statistical software, Python allows for more scalable, reproducible, and customisable workflows, thereby making it particularly well-suited for portfolio optimisation tasks that involve matrix operations, constraint handling, and iterative algorithms.

The first step of this analysis involves turning daily prices into daily discrete returns. After this, by computing their means and standard deviations, daily expected returns and daily volatilities are obtained respectively. These values are then annualised, considering 252 trading days per year, in order to obtain annual expected returns and annual volatilities.

Annual expected returns:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

$$E(R_i) = \mu = \frac{1}{T}\sum_{t=1}^{T} R_{it}$$

$$E(R_{\text{year}}) = (1 + E(R_{\text{day}}))^{252} - 1$$

Annual volatilities:

$$\sigma^2 = \frac{1}{T}\sum_{t=1}^{T}(R_t - \mu)^2$$

$$\sigma = \sqrt{\sigma^2}$$

$$\sigma_{year} = \sigma_{day} \cdot \sqrt{252}$$

Following this, the covariance matrix, that which captures the variances of individual asset returns (diagonal elements) and the covariances between pairs of asset returns (off-diagonal elements), is computed as it will be required to computer portfolio volatilities. Moreover, the variable “weights”, which represents the proportion of capital allocated to each asset in the portfolio, is defined, as it constitutes a key parameter in the optimisation process that follows. Two constraints are imposed on this variable: (1) the total sum of the weights must equal 1 (100%), ensuring all capital is fully invested, and (2) weights cannot be negative, thereby prohibiting short-selling.

Covariance matrix:

$$[\sigma_{ij}] = \rho_{ij} \cdot \sigma_i \cdot \sigma_j$$

Constraint (1):

$$\sum_{i=1}^{n} w_i = 1$$

Constraint (2):

$$0 \leq w_i \leq 1$$

Following this, the risk-free rate applicable to each portfolio, an essential input for calculating portfolio Sharpe Ratios, is computed using a weighted average approach. Specifically, the 10-year treasury bond yield of each region is applied in proportion to that region's weight within each portfolio for each year.

$$\text{total\_rf} = W_{AMERICA} * RF_{AMERICA} + W_{ASIA\text{-}PACIFIC} * RF_{ASIA\text{-}PACIFIC} + W_{EUROPE} * RF_{EUROPE}$$

The subsequent step consists of calculating portfolio returns and portfolio volatilities through matrix-based calculations, which are needed to obtain the portfolio Sharpe Ratios. These computations make it possible to assess how each portfolio performs in terms of risk-adjusted returns and also allow for meaningful comparisons across different portfolios, ultimately aiding in the selection of the most efficient ones.

Portfolio return:

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i)$$

$$E(r_p) = \vec{w}_i \cdot \vec{R}_i$$

Portfolio volatility:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}$$

$$\sigma_p^2 = \vec{w}_i \cdot [\sigma_{ij}] \cdot \vec{w}_i^{\,T}$$

Portfolio Sharpe Ratio:

$$\text{Sharpe}_p = \frac{R_p - r_f}{\sigma_p}$$

The final step entails identifying the portfolio that maximises the Sharpe Ratio using the Sequential Least Squares Programming (SLSQP) optimisation algorithm. As Python's optimisation libraries are designed to minimise objective functions, the problem is reformulated by minimising the negative Sharpe Ratio, which effectively achieves the same outcome as maximisation.

5 RESULTS

This section analyses the Sharpe Ratio as well as its individual components, namely returns, volatilities, and risk-free rates, within the macroeconomic and geopolitical events of the selected period to provide an enhanced understanding of the financial performance trends of both the constructed AI-related sectoral portfolios and benchmark indices. Additionally, it explores yearly optimal company allocations, thereby offering insights into the best performing risk-return profiles.

5.1 SECTOR-BASED OPTIMAL PORTFOLIO ANALYSIS: KEY METRICS

Table 2: Optimal portfolios and indices analysis metrics: Returns, Volatilities and Risk-free rates

	2020			2021			2022		
	R	V	Rf	R	V	Rf	R	V	Rf
Software	368.33%	37.56%	1.073%	107.15%	20.95%	1.491%	25.57%	35.98%	2.690%
Hardware	223.01%	39.33%	1.893%	264.37%	24.41%	2.186%	96.44%	51.62%	2.799%
Others	1119.29%	89.46%	1.115%	51.97%	18.83%	1.618%	-4.12%	72.75%	2.938%
S&P 500	20.51%	16.88%	0.884%	30.71%	7.08%	1.440%	-17.99%	13.58%	2.957%
CSI 300	42.72%	12.78%	2.969%	-3.69%	11.16%	3.038%	-25.85%	13.75%	2.783%
DAX	19.24%	16.73%	-0.478%	8.59%	8.58%	-0.311%	-13.10%	15.08%	1.185%

	2023			2024		
	R	V	Rf	R	V	Rf
Software	308.34%	32.79%	3.548%	159.29%	22.53%	3.606%
Hardware	288.45%	27.25%	3.283%	164.15%	27.84%	3.149%
Others	118.84%	29.77%	3.829%	123.96%	25.42%	3.974%
S&P 500	25.30%	7.24%	3.965%	29.24%	6.98%	4.185%
CSI 300	-15.19%	8.76%	2.743%	42.42%	8.85%	2.292%
DAX	23.72%	9.14%	2.463%	22.70%	8.01%	2.368%

Source: Own elaboration

At first glance, risk-free rates have gradually increased over time, while the returns and volatilities of the constructed optimal portfolios and selected benchmark indices have fluctuated markedly throughout the analysed timeframe, underscoring the dynamic interplay between technological advancements, macroeconomic forces, and geopolitical shifts.

The explosive growth observed in 2020, particularly within the 'Others' sector, can be attributed to the convergence of various booms triggered by the COVID-19 pandemic. Supporting the findings of other studies, healthcare and pharmaceutical companies experienced substantial growth during the pandemic, benefitting from global investments aimed at curing patients, preventing virus transmission, and developing effective treatments and vaccines (Esparcia & López, 2022). However, the standout driver of the portfolio's performance was Tesla. Its meteoric rise was fueled by factors including its inclusion in the S&P 500 index, the announcement of strategic stock splits, and strong investment enthusiasm fueled by the company's leadership in both technological innovation and electric vehicles amidst favourable market conditions. (Klinge et al., 2025). The Software and Hardware sectors also demonstrated impressive financial performance, offering compelling risk-return profiles that underscore their critical roles during the COVID-19 pandemic, which marked an era of rapid digital transformation. On the one hand, the Software sector exemplified the urgent demand for digital solutions to adapt to remote work, virtual services, and evolving operational needs. On the other hand, the Hardware sector benefited from an increase in demand for the physical infrastructure required to support this accelerated digital shift. Conversely, the benchmark indices exhibited comparatively more moderate financial performance, likely due to their broader sectoral diversification and comparatively lower exposure to AI-related companies.

In 2021, although overall financial performance moderated from the unprecedented highs recorded in 2020, the analysed sectors continued to demonstrate robust results, with the Hardware sector emerging as the most notable outperformer. This shift can be attributed to an imbalance between constrained semiconductor supply and rising demand for components essential to technological advancement. This mismatch was triggered by the COVID-19 pandemic, which resulted in several disruptions including factory shutdowns, labour shortages, and strict government restrictions, which collectively caused severe bottlenecks in semiconductor production and distribution (Frieske & Stieler, 2022; Ochonogor et al., 2023). While this intensified global competition for semiconductor components, it also created an increase in demand-driven pricing, which benefitted firms that secured inventory and fulfilled delivery obligations, helping them maintain strong market positions despite widespread disruption (Frieske & Stieler, 2022; Ochonogor et al., 2023). Conversely, both the DAX and CSI 300 indices recorded declines in financial performance, whereas the S&P 500 index recorded improvements. This strong performance was driven by diverse factors, including an economic rebound following the COVID pandemic and unprecedented fiscal and monetary support. Massive government stimulus packages, such as the American Rescue Plan, boosted consumer spending and business activity (IMF, 2021), while the Federal Reserve maintained near-zero interest rates and continued large-scale asset purchases (BIS, 2023). Additionally, the index's heavy weighting in high-performing technology companies further amplified its gains, as investors remained confident in the long-term prospects of digital and innovation-driven sectors.

In contrast to the remarkable financial growth observed in previous years, 2022 marked a notable downturn across all sectors and indices. Although the analysed sectors continued to deliver positive returns, the benchmark indices recorded negative performance over the same period. This decline can be attributed to several factors, including geopolitical conflicts like the Russia-Ukraine war and the announcement of regulatory frameworks like the EU AI Act. On the one hand, the Russia-Ukraine conflict disrupted several industries worldwide by severely impacting energy and food supply chains, since both involved nations are key exporters of fossil fuels, grains, and fertilisers, (Gehrmann et al., 2025; FAO, 2022). This disruption resulted in spikes in commodity prices and inflation, which contributed to economic downturns, particularly in import-dependent regions (FAO, 2022; IMF, 2023). The heightened economic uncertainty negatively impacted the financial performance of both corporations and indices as investors shifted their capital into defense-related firms, driven by the military nature of the conflict, as well as safer investment alternatives, thereby reducing exposure to higher-risk sectors (Gehrmann et al., 2025). On the other hand, the European Union's announcement of the AI Act, the world's first comprehensive AI regulatory framework, introduced compliance challenges and marked an important turning point in industry governance, thus further exacerbating uncertainty in the AI investment landscape (Fernández-Llorca et al., 2024).

In response to inflationary pressures, major central banks, including the U.S. Federal Reserve and the European Central Bank (ECB) implemented interest rate hikes, reflecting changing market expectations (IMF, 2023). Changes in risk-free rates influence the financial performance of other asset classes. Higher risk-free rates increase the discount rate applied to future cash-flows, thereby reducing the present value of growth-oriented firms whose valuations heavily depend on long-term earnings projections (Koroleva & Kopeykin, 2022). This environment also raises the cost of capital, thereby constraining innovation, especially amongst smaller or early-stage firms (Czarnitzki & Binz, 2009). Furthermore, elevated rates also alter market sentiment, prompting shifts from speculative, high-growth investment choices to safer, income-generating alternatives (Baker et al., 2016).

In 2023, the global financial landscape experienced an exceptional recovery, influenced by advancements in AI, particularly the introduction of Generative Pre-trained Transformers (GPT). Widely adopted by individuals and businesses alike, GPT models like OpenAI's ChatGPT and Google's Gemini elevated investor expectations, positioning companies that either developed or implemented these technological advancements as the most sought-after in the market (Trautman et al., 2023). Their broad applicability largely accounts for the substantial growth observed across all analysed sectors and indices. Companies in the Software sector, inspired by GPT models, accelerated the development of AI-driven solutions that either extended, complemented, or served as alternatives to these technologies (Singla et al., 2025). The Hardware sector also thrived thanks to rising demand for high-performance computational infrastructure, essential for the training, deployment and operation of these tools. Meanwhile, companies in the 'Others' category also benefited from integrating these technologies into their operations, which helped streamline workflows, boost productivity, and enable enhanced data-driven decision-making. Both the S&P500 and DAX indices likewise benefited from recent technological advancements, as their portfolios included companies at the forefront of AI innovation. In contrast, the CSI 300 index continued to lag behind, reflecting limited exposure to globally leading AI firms and the comparatively slower pace of AI development amongst Chinese companies.

Finally, in 2024, the financial performance of the analysed AI-related sectors began to moderate as the initial hype surrounding GPTs subsided and market participants better understood their long-term potential. Conversely, the performance of the analysed benchmark indices remained relatively stable, with the notable exception of the CSI 300 index. This outperformance was likely driven by fiscal and monetary stimulus measures introduced by the Chinese government, including reductions in bank reserve requirements, interest rate cuts, and increased public spending (World Bank, 2024). These interventions supported industrial output, strengthened business confidence, and sustained broader economic momentum amidst structural challenges. Additionally, China's focused investment in high-tech manufacturing and infrastructure, combined with resilient export performance, further contributed to the index's upward trajectory (World Bank, 2024).

In conclusion, the observed correlation between AI-related sectors and benchmark indices is unsurprising, given that many leading AI firms are also constituents of these broader indices. This structural overlap explains their similar responses to macroeconomic and geopolitical developments, reflecting the interconnected nature of global financial markets. However, AI-related sectors outperformed the benchmarks due to concentrated gains amongst top-performing AI firms, while broader index diversification diluted their exposure to this growth. This divergence in performance highlights the strength and momentum of AI-focused firms, reaffirming their position as high-potential, strategically valuable investment opportunities.

5.2 COMPANY ALLOCATION & DISTRIBUTION BY SECTOR AND REGION

As will be demonstrated, the constructed optimal portfolios reflect an ever-evolving pattern of company selection and allocation over the analysis period, capturing the complex and multifaceted impacts of technological advancements, macroeconomic shifts, and geopolitical events. These optimal portfolios highlight noteworthy transformations across sectors, revealing varied and asymmetric responses to shifting global conditions.

5.2.1 COMPANY ALLOCATION AND DISTRIBUTION BY SECTOR AND REGION: SOFTWARE

Table 3: Software sector constituents and their weights, returns, and volatilities 2020-2024

Software 2020				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Accenture	ACN-US	27.81%	388.81%	58.81%
Cloudflare	NET-US	19.93%	463.11%	69.38%
Zscaler	ZS-US	14.04%	431.15%	69.56%
RAKUnited States	3923-JP	13.64%	217.89%	64.16%
MicroStrategy	MSTR-US	9.02%	222.14%	61.02%
Pinterest	PINS-US	4.69%	388.08%	83.52%
BILL Holdings	BILL-US	4.26%	380.54%	79.90%
Crowdstrike Holdings	CRWD-US	4.24%	428.97%	65.47%
Crayon	CRAYN-NO	2.36%	210.42%	70.51%

Software 2021				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Fortinet	FTNT-US	41.68%	163.64%	35.39%
Accenture	ACN-US	17.32%	65.07%	19.67%
Alphabet (Google)	GOOGL-US	14.35%	73.16%	24.31%
NAVER	035420-KR	7.89%	25.29%	34.85%
Teradata	TDC-US	7.07%	145.83%	73.94%
Capgemini	CAP-FR	4.87%	58.30%	22.85%
Oracle	ORCL-US	2.06%	42.78%	29.23%
IBM	IBM-US	1.56%	16.09%	23.17%
Wangsu Science & Technology	300017-CN	1.49%	6.29%	40.41%
RAKUnited States	3923-JP	0.90%	36.55%	55.08%
Box	BOX-US	0.82%	58.79%	39.17%

Software 2022				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Box	BOX-US	94.40%	26.79%	37.96%
China Tower	788-HK	5.50%	4.76%	34.69%

Software 2023				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Meta (Facebook)	META-US	29.28%	209.49%	39.83%
SAKURA Internet	3778-JP	22.33%	511.45%	86.66%
MicroStrategy	MSTR-US	21.63%	475.09%	73.12%
Crowdstrike Holdings	CRWD-US	10.15%	172.38%	41.68%
Nextdc	NXT-AU	5.07%	62.17%	27.87%
Wangsu Science & Technology	300017-CN	4.65%	52.53%	48.71%
Salesforce	CRM-US	4.58%	105.42%	29.61%
Elastic	ESTC-US	1.02%	167.13%	60.07%
SoftwareOne	SWON-CH	0.56%	40.85%	32.44%
IBM	IBM-US	0.49%	17.26%	16.16%
Cogent Communications Holdings	CCOI-US	0.24%	38.46%	30.84%

Software 2024				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Tencent	700-HK	17.08%	83.60%	29.10%
China Tower	788-HK	15.55%	46.78%	29.98%
Oracle	ORCL-US	14.92%	104.88%	33.23%
IBM	IBM-US	14.82%	56.80%	23.22%
MicroStrategy	MSTR-US	11.72%	488.73%	107.33%
SAKURA Internet	3778-JP	10.57%	386.57%	112.65%
Meta (Facebook)	META-US	7.36%	112.09%	39.43%
Crayon	CRAYN-NO	6.31%	103.16%	53.88%
Wangsu Science & Technology	300017-CN	1.41%	46.37%	49.89%
Nextdc	NXT-AU	0.25%	52.38%	33.93%

Source: Own elaboration

In 2020, the software portfolio was fully allocated to Software and Consulting. The US accounted for the majority share (56.20%), followed by China (27.80%), Japan (13.65%), and Norway (2.35%). The 2021 portfolio maintained its exclusive focus on Software and Consulting, with the US further strengthening its dominance (84.85%), while other notable regions included South Korea (7.90%), France (4.85%), China (1.50%), and Japan (0.90%). In 2022, the portfolio introduced sectoral diversification, comprising Software and Consulting (94.40%) and Telecommunications (5.60%). Geographically, the portfolio was heavily weighted toward the US (94.40%), with China representing the remaining share (5.60%). The 2023 portfolio remained largely concentrated in Software and Consulting (99.75%), with a minor allocation to Telecommunications (0.25%). The

US continued to lead (67.40%), followed by Japan (22.33%), Australia (5.05%), China (4.66%), and Switzerland (0.55%). By 2024, the portfolio was more balanced, with allocations spanning Software and Consulting (84.45%) and Telecommunications (15.55%). The US held the largest share (48.80%), followed by China (34%), Japan (10.55%), Norway (6.40%), and Australia (0.25%).

This analysis highlights two noteworthy trends. Firstly, while the US remains the leading country in software-related activities, its dominance appears increasingly challenged by strong competitors from East Asia, most notably China, Japan, and South Korea. These countries have expanded their presence in AI-related portfolios, reflecting their growing technological capabilities and strategic positioning in the global digital economy. Secondly, sectoral diversification is steadily increasing. Although Telecommunications still accounts for a smaller number of companies, its increasing allocation underscores its growing strategic role in AI deployment, particularly in enabling connectivity, data transmission, and underlying infrastructure.

5.2.2 COMPANY ALLOCATION AND DISTRIBUTION BY SECTOR AND REGION: HARDWARE

Table 4: Hardware sector constituents and their weights, returns, and volatilities 2020-2024

Hardware 2020				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Unigroup Guoxin Microelectronics	002049-CN	31.33%	250.28%	65.28%
Asmedia Technology	5269-TW	19.28%	240.48%	67.74%
Alchip Technologies	3661-TW	18.93%	266.76%	71.29%
Lattice Semiconductor	LSCC-US	17.58%	176.48%	56.92%
Advanced Micro Devices	AMD-US	4.86%	124.24%	60.85%
NVIDIA	NVDA-US	4.43%	157.39%	57.92%
Vertiv	VRT-US	3.48%	102.11%	62.11%
Western Digital	WDC-US	0.11%	130.18%	48.04%

Hardware 2021				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Faraday Tech	3035-TW	22.85%	529.01%	71.16%
GDS	GD-US	20.92%	45.23%	17.47%
Arista Networks	ANET-US	17.63%	115.07%	33.92%
Hunan Goke Microelectronics	300672-CN	15.43%	551.81%	87.56%
NVIDIA	NVDA-US	10.88%	148.67%	45.07%
Seagate Technology	STX-US	7.22%	103.18%	39.04%
COMET Holding AG	COTN-CH	3.15%	76.56%	36.88%
Amlogic	688099-CN	1.08%	104.70%	51.34%
Ambarella	AMBA-US	0.83%	170.09%	63.25%

Hardware 2022				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Super Micro Computer	SMCI-US	73.60%	122.72%	66.52%
GDS	GD-US	26.40%	23.13%	23.55%

Hardware 2023				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Alchip Technologies	3661-TW	22.34%	385.99%	56.93%
Vertiv	VRT-US	17.40%	323.94%	55.51%
Jeju Semiconductor	080220-KR	15.06%	390.41%	67.82%
Palo Alto Networks	PANW-US	8.86%	130.90%	38.32%
Camtek	CAMT-US	7.16%	248.80%	46.33%
Super Micro Computer	SMCI-US	6.64%	352.73%	75.13%
Yokogawa Electric	6841-JP	4.49%	28.04%	29.35%
Asmedia Technology	5269-TW	4.25%	211.94%	55.14%
Wuhan Jingce Electronic	300567-CN	4.05%	96.84%	53.83%
ADTechnology	200710-KR	3.60%	235.83%	66.47%
NVIDIA	NVDA-US	2.63%	292.42%	48.46%
VIA Technologies	2388-TW	1.93%	192.42%	65.02%
GDS	GD-US	1.57%	6.23%	18.22%

Hardware 2024				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
NVIDIA	NVDA-US	37.08%	307.20%	56.83%
GDS	GD-US	18.24%	24.95%	16.03%
Taiwan Semiconductor Manufacturing	2330-TW	17.81%	103.42%	38.19%
Vertiv	VRT-US	7.38%	236.32%	57.07%
Western Digital	WDC-US	5.37%	52.38%	33.93%
Ingenic Semiconductor	300223-CN	4.40%	22.70%	55.65%
Allwinner Technology	300458-CN	4.21%	72.32%	60.09%
Yokogawa Electric	6841-JP	2.95%	60.59%	33.33%
Transcend Info	2451-TW	2.56%	46.07%	32.30%

Source: Own elaboration

In 2020, the Hardware sector was dominated by Electronic Components & Manufacturing (87.10%), followed by Hardware (9.40%), and Industrial Manufacturing (3.50%). The largest exposure was to Taiwan (38.20%), followed by China (31.35%) and the US (30.45%). By 2021, the portfolio was more balanced between Hardware (57.50%) and Electronic Components and Manufacturing (42.50%). The US led (57.50%), while Taiwan (22.85%), China (16.50%), and Switzerland (3.15%) remained noteworthy contributors. In 2022, the portfolio was fully concentrated in Hardware and entirely based in the US. Diversification returned in 2023, with Electronic Components and Manufacturing (62.90%), Hardware (19.70%), and Industrial Manufacturing (17.40%). The US

(37.10%) remained dominant, followed by Taiwan (28.50%) and South Korea (18.65%), with smaller allocations to Israel (7.15%), Japan (4.50%), and China (4.05%). By 2024, the portfolio consolidated again, with Hardware (60.90%), Electronic Components and Manufacturing (31.60%), and Industrial Manufacturing (7.35%), led by the US (68.25%), with representation from Taiwan (20.35%), China (8.60%), and Japan (2.60%).

This analysis highlights two key trends. On the one hand, while the US remains central to hardware-related activities, its dominance is increasingly shared with some East Asian countries, particularly Taiwan, China, and South Korea, who have shown strength in semiconductor manufacturing and component innovation. On the other hand, the portfolio exhibits increasing subsector diversification, with greater exposure to electronic components and industrial manufacturing, highlighting the need to focus on both core processing technologies and the infrastructure necessary to support AI systems.

5.2.3 COMPANY ALLOCATION AND DISTRIBUTION BY SECTOR AND REGION: ‘OTHERS’

Table 5: ‘Others’ sector constituents and their weights, returns, and volatilities 2020-2024

Others 2020				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Tesla	TSLA-US	100.00%	1119.29%	89.46%

Others 2021				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
SBA Communications	SBAC-US	49.51%	44.48%	21.05%
RadNet	RDNT-US	19.05%	83.09%	49.94%
Intuitive Surgical	ISRG-US	10.57%	40.11%	27.66%
Digital Realty Trust	DLR-US	8.72%	34.02%	21.85%
Tesla	TSLA-US	7.90%	68.01%	54.77%
American Tower	AMT-US	4.25%	36.09%	20.25%

Others 2022				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
Alibaba	9988-HK	100.00%	-4.12%	72.75%

Others 2023				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
RadNet	RDNT-US	38.83%	100.88%	36.74%
Tesla	TSLA-US	32.99%	166.20%	52.65%
Amazon	AMZN-US	28.18%	88.16%	33.03%

Others 2024				
Name	**Ticker**	**Weights**	**Return**	**Volatility**
RadNet	RDNT-US	46.38%	178.12%	41.69%
Alibaba	9988-HK	25.96%	84.21%	37.66%
Intuitive Surgical	ISRG-US	25.21%	76.19%	26.53%
American Tower	AMT-US	2.46%	11.58%	23.51%

Source: Own elaboration

Finally, the 'Others' portfolio experienced significant shifts in both sectoral composition and geographic allocation between 2020 and 2024. In 2020, the portfolio was entirely concentrated in Consumer Vehicles and Parts, solely through Tesla, with full exposure to the US. In 2021, it diversified across Real Estate (62.50%), Healthcare Services (19.10%), and Consumer Vehicles and Parts (7.90%), while remaining fully allocated to US-based firms. In 2022, the portfolio shifted entirely to Food and Staples Retail (100%), exclusively through Alibaba, resulting in full exposure to China. Diversification resumed in 2023, with allocations across Healthcare Services (38.80%), Consumer Vehicles and Parts (33.00%), and Food and Staples Retail (28.20%), all represented by US companies. By 2024, the portfolio remained diversified, with an emphasis on health-related companies, specifically Healthcare Services (46.40%) and Healthcare Equipment (25.20%). The rest was invested in Food and Staples Retail (26.00%) and Real Estate (2.50%), with geographic exposure split between the US (74.00%) and China (26.00%).

This analysis reveals two key developments within the 'Others' portfolio. Firstly, while the US remained the dominant geographical focus throughout the period, exposure to China indicates an expansion of geographic scope and an increasing recognition of emerging market opportunities. Secondly, the portfolio evolved into a more diversified structure, indicating a strategic pivot toward other essential and resilient sectors.

5.3 OPTIMAL PORTFOLIOS AND INDICES ANALYSIS: SHARPE RATIOS

Table 6: Optimal portfolios and indices analysis metrics: Sharpe Ratio

	Sharpe Ratio								
	2020	2021	2022	2023	2024	Min	Max	Mean	Max - Min
Software	9.78	5.04	0.64	9.30	6.91	0.64	9.78	6.33	9.14
Hardware	5.62	10.74	1.81	10.46	5.78	1.81	10.74	6.88	8.93
Others	12.50	2.67	-0.10	3.86	4.72	-0.10	12.50	4.73	12.60
S&P 500	1.16	4.14	-1.54	2.95	3.59	-1.54	4.14	2.06	5.68
CSI 300	3.11	-0.60	-2.08	-2.05	4.53	-2.08	4.53	0.58	6.62
DAX	1.18	1.04	-0.95	2.33	2.54	-0.95	2.54	1.23	3.49

Source: Own elaboration

Although returns, volatilities, and risk-free rates offer useful insights into portfolio behaviour, they fall short in enabling direct comparisons between different investment alternatives. The Sharpe Ratio overcomes this limitation by integrating these elements into a single, standardised measure of risk-adjusted performance, highlighting the excess return achieved relative to the risk undertaken.

Although some sectors may outperform others in specific years, the selection of an optimal portfolio ultimately depends on the evaluation framework applied. A year-by-year analysis may emphasise short-term fluctuations, whereas assessing aggregate metrics, like the mean, minimum, maximum, and spread values, captures overall risk-adjusted performance more effectively.

Furthermore, while both Hardware and Software demonstrate strong risk-adjusted performance, Hardware slightly outperforms Software by achieving higher minimum, maximum, and average Sharpe Ratios, alongside a narrower range between those extremes, signalling a more stable risk-return profile. Their ability to sustain elevated Sharpe Ratios during periods of macroeconomic instability highlights their defensive strength and long-term investment appeal, reinforcing their relevance for investors targeting growth opportunities in the tech sector. Conversely, the 'Others' category recorded the lowest minimum, maximum, and average Sharpe Ratios, along with the widest fluctuations, underscoring its underperformance relative to the other sectors analysed.

When compared to the benchmark indices, despite displaying greater performance variability, as reflected in the broader spreads in their min-max ranges, the analysed AI-related sectors still demonstrate superior risk-adjusted financial performance, as evidenced by lower minimum, higher maximum, and higher mean Sharpe Ratios across all evaluated years (2020-2024).

In conclusion, the analysed sectors clearly demonstrate superior risk-adjusted financial performance relative to the selected benchmark indices, reinforcing their appeal as compelling and worthwhile investment opportunities. Furthermore, it can also be concluded that both Hardware and Software position themselves as the most compelling investment choices given their ability to provide resilient financial performance. Two mutually reinforcing dynamics form the basis of this projection. On the one hand, both sectors are witnessing intensified competition, particularly driven by growing participation from the US and East Asia, including China, Taiwan, South Korea, and Japan, with more firms than ever advancing rapidly in pursuit of technological leadership, which in turn drives unprecedented innovation. On the other hand, the inherent synergy between the sectors reinforces their joint momentum, as progress in software development amplifies the need for advanced computing infrastructure, while hardware innovations enable the creation of increasingly complex and capable software solutions.

6 CONCLUSION

This study demonstrates that applying Modern Portfolio Theory (MPT) and the Sharpe Ratio to AI-focused sectors provides an empirically grounded perspective on financial behaviour, effectively bridging academic analysis with practical investment relevance. By contextualising performance trends with key macroeconomic and geopolitical events, this project offers valuable guidance for investors, researchers, and policymakers navigating an increasingly AI-driven global economy. As technological innovation accelerates amidst ongoing uncertainty, these insights lay an understanding foundation for assessing the long-term potential and strategic relevance of AI-focused investments.

This project offers a distinctive contribution by linking performance trends to major global events, thereby delivering strategic insights that support informed, context-driven investment decisions. For investors, the findings support the development optimal portfolios, while also reinforcing the case for AI-focused companies as compelling investment choices. For policymakers, this project reveals the interplay between innovation, macroeconomic disruptions, and regulation in shaping financial performance, offering insights to guide policies and regulations by distinguishing between sectors capable of self-sustained growth from those requiring public intervention to remain competitive.

On the one hand, the analysis highlights the financial strength of the Hardware and Software sectors, where intensifying competition, particularly from the U.S. and East Asia, including China, Taiwan, South Korea, and Japan, has accelerated innovation. In this context, hardware advancements provide the necessary infrastructure for software development, whereas software progress fuels demand for increasingly advanced hardware, creating a cycle of mutual reinforcement. Conversely, the 'Others' sector continues to deliver strong risk-adjusted financial performance, underscoring AI’s broad applicability across diverse industries worldwide. Consequently, given their comparatively appeal, targeted policy support may be necessary in the 'Others' sector alongside Europe to enhance their competitiveness and ensure balanced progress across the AI ecosystem.

On the other hand, the analyses highlight the anticipated correlation between the AI-related sectors and benchmark indices, attributable to the significant overlap in their constituent firms, highlighting their synchronised sensitivity to macroeconomic and geopolitical developments. Nevertheless, AI-related sectors outperformed the indices, underscoring the momentum behind AI-focused companies and reinforcing their appeal as high-potential, strategically significant investment opportunities.

Nonetheless, several limitations warrant consideration. This study is grounded in historical data from 2020 to 2024, a period characterised by significant opportunity and uncertainty. Consequently, the conclusions drawn reflect the dynamics of a highly specific and transitional context, which may not fully generalise to future conditions. Moreover, the portfolio analysis employed a retrospective, static framework, thereby offering valuable insights into past performance, but lacking predictive or adaptive modelling capabilities. Additionally, sector classifications, while analytically practical, may oversimplify the complex, cross-cutting nature of AI firms operating across multiple domains.

To build on this foundation, future research should adopt forward-looking methodologies that better capture the dynamic nature of AI markets. Approaches such as adaptive allocation strategies and predictive modeling attuned to shifting market conditions can provide deeper, more actionable insights. Additionally, refining sector classifications, by introducing sub-sector delineations or capability-based taxonomies, may uncover subtler patterns within the diverse and rapidly evolving AI ecosystem. Expanding the temporal scope of analysis and investigating the interdependencies between AI developments and macroeconomic forces will be crucial for understanding the long-term trajectory of AI-focused investment strategies. Finally, broadening the range of indices employed could enhance company coverage, increase analytical robustness, and offer a stronger rationale for the selection of the study period.

7 APPENDIX

ANNEX 1: PYTHON CODE

The following code forms the foundation of the process for calculating optimal portfolios that maximise the Sharpe ratio. It is designed to be fully generalisable and adaptable: by specifying the parameters PF_ASSETS, PF_SINCE, and PF_UNTIL, the corresponding optimal portfolio can be generated.

A. IMPORT LIBRARIES

```
from math import sqrt
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import random
from scipy.optimize import minimize
from scipy.stats import uniform
import statsmodels.api as sm
```

B. LOAD DATA

```
data = pd.read_excel('aquel.xlsx',index_col='Fecha')
data
```

```
print(data.columns.tolist())
```

C. FILTER DATA

```
# Select companies:
PF_ASSETS = ["XXX-XX"]
PF_NUM_ASSETS = len(PF_ASSETS)
prices = data[PF_ASSETS]

# Select dates
PF_SINCE = "yyyymmdd"
PF_UNTIL = "yyyymmdd"

# Risk-free rate (10-year treasury bonds)
risk_free_rate = x.xxx # (x.xx%)

# Filter data:
dates = (data.index >= PF_SINCE) & (data.index <= PF_UNTIL)
prices = prices.loc[dates, :]
prices
```

D. DATA ANALYSIS

```
prices.describe()
```

E. PLOT: HISTORICAL STOCK PRICE COMPARISONS - MAXIMUM SHARPE RATIO

```python
def plot_stocks(tickers, df):
    plt.figure(figsize=(12, 6))

    for ticker in tickers:
        if ticker in df.columns:
            plt.plot(df.index, df[ticker], label=ticker, linewidth=2)
        else:
            print(f"Ticker {ticker} not found in the dataset.")

    plt.xlabel('Date')
    plt.ylabel('Stock Price')
    plt.title('Historical Stock Prices Comparison: Maximum Sharpe Ratio')

    plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

    plt.grid(True)
    plt.show()

tickers = ['XXX-XX']

plot_stocks(tickers, prices)
```

F. CALCULATIONS

```python
# Daily discrete return:
def daily_returns(prices):
    returns = pd.DataFrame(index=prices.index, columns=prices.columns)
    for col in prices.columns:
        clean_series = prices[col].dropna()
        clean_returns = clean_series.pct_change()
        returns.loc[clean_returns.index, col] = clean_returns
    return returns.astype(float)

# Expected annual return:
def expected_returns(prices):
    dr = daily_returns(prices)
    avg_daily = dr.mean()
    return (1 + avg_daily) ** 252 - 1

# Annual volatility:
def volatilities(prices):
    dr = daily_returns(prices)
    return dr.std() * np.sqrt(252)

# Covariance matrix:
def covariance_matrix(prices):
    dr = daily_returns(prices)
    dr_clean = dr.dropna(axis=1, thresh=30)
    return 252 * dr_clean.cov(numeric_only=True)

# Correlation matrix (optional):
def correlation_matrix(prices):
    dr = daily_returns(prices)
    dr_clean = dr.dropna(axis=1, thresh=30)
    return dr_clean.corr(numeric_only=True)

# Portfolio expected return:
def portfolio_return(weights, expected_returns):
    return np.dot(weights, expected_returns)

# Portfolio volatility:
def portfolio_volatility(weights, cov_matrix):
    return np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
```

```python
# Portfolio Sharpe ratio:
def portfolio_sharpe_ratio(port_return, port_volatility, risk_free_rate):
    return (port_return - risk_free_rate) / port_volatility
```

F1. ANNUAL EXPECTED RETURNS

```
returns = expected_returns(prices)
returns
```

F2. ANNUAL VOLATILITIES

```
vols = volatilities(prices)
vols
```

F3. COVARIANCE MATRIX

```
returns = expected_returns(prices)
vols = volatilities(prices)
cov_matrix = covariance_matrix(prices)

pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)
print("Covariance matrix shape:", cov_matrix.shape)

cov_matrix
```

```
cov_matrix = covariance_matrix(prices)
cov_matrix_plot = cov_matrix.round(3)

fig = px.imshow(
    cov_matrix_plot,
    text_auto=True,
    width=900,
    height=900,
    color_continuous_scale="Viridis")

fig.update_layout(title="Covariance Matrix")
fig.show()
```

F4. CORRELATION MATRIX

```
corr_matrix = correlation_matrix(prices)

pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)
print("Correlation matrix shape:", corr_matrix.shape)

corr_matrix
```

```
corr_matrix = daily_returns(prices).corr()
corr_matrix_plot = corr_matrix.round(3)

fig = px.imshow(
    corr_matrix_plot,
    text_auto=True,
    zmin=-1, zmax=1,
    width=900, height=900,
    color_continuous_scale='RdBu')

fig.update_layout(title="Correlation Matrix")
fig.show()
```

G. MAXIMYM SHARPE RATIO PORTFOLIO

```
def _neg_sharpe_ratio(weights, returns, cov_matrix, risk_free_rate):

    pf_ret    = portfolio_return(weights, returns)
    pf_vol    = portfolio_volatility(weights, cov_matrix)
    pf_sharpe = portfolio_sharpe_ratio(pf_ret, pf_vol, risk_free_rate)

    return - pf_sharpe

def maximize_sharpe_ratio(returns, cov_matrix, risk_free_rate):

    num_assets = len(returns)
    initial_guess = num_assets*[1./num_assets,]
    args = (returns, cov_matrix, risk_free_rate)

    # all weights must add up to 1.0
    constraints = ({'type': 'eq', 'fun': lambda x: x.sum() - 1})

    # bounded by 0 and 1
    bound = (0.0,1.0)
    bounds = tuple(bound for asset in range(num_assets))

    # optimize
    result = minimize(_neg_sharpe_ratio,
                      initial_guess,
                      args=args,
                      method='SLSQP',
                      bounds=bounds,
                      constraints=constraints)

    print(result.message)

    return pd.Series(result.x, index=returns.index).sort_values(ascending=False)
```

```
# Optimize
max_sharpe_weights = maximize_sharpe_ratio(returns, cov_matrix, risk_free_rate)

# FIX: align returns & cov matrix
returns = returns.loc[max_sharpe_weights.index]
cov_matrix = cov_matrix.loc[max_sharpe_weights.index, max_sharpe_weights.index]

# Calculate return and volatility
max_sharpe_ret = portfolio_return(max_sharpe_weights, returns)
max_sharpe_vol = portfolio_volatility(max_sharpe_weights, cov_matrix)

print('OPTIMIZATION')
print(f'The Maximum Sharpe Portfolio has Return = {max_sharpe_ret:.2%} and Volatility = {max_sharpe_vol:.2%}')
print('\nAnd the following composition:')
for i in max_sharpe_weights.index:
    print(f'{i}\t{max_sharpe_weights[i]:03.2%}')
```

Declaración de Uso de Herramientas de IA Generativa en Trabajos Fin de Grado

Por la presente, yo, Guillermo Cavero Sánchez, estudiante de ADE y Business Analytics de la Universidad Pontificia Comillas (ICADE), al presentar mi Trabajo Fin de Grado titulado "Analysing companies that invest in Artificial Intelligence using Markowitz and Sharpe", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. **Referencias:** Usado conjuntamente con otras herramientas, como Science, para identificar referencias preliminares que luego he contrastado y validado.
2. **Corrector de estilo literario y de lenguaje**: Para mejorar la calidad lingüística y estilística del texto.
3. **Revisor**: Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para qué se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 2 de junio de 2025

Firma: Guillermo Cavero Sánchez

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