Islamic Business & Management

IJIBM VOL 7 NO 1 (2023) P-ISSN 2576-7674 E-ISSN 2576-7682

Available online at https://www.cribfb.com
Journal homepage: https://www.cribfb.com/journal/index.php/ijibm
Published by CRIBFB, USA

AI-DRIVEN CAPITAL ASSET PRICING MODEL FOR ENHANCING SHARIAH-COMPLIANT INVESTMENT DECISIONS – A CHINESE STOCK MARKET ANALYSIS

Klemens Katterbauer [(a)1] *Hassan Syed* [(b)] *Laurent Cleenewerck* [(c)] *Sema Yilmaz Genc* [(d)]

[(a)] *Professor, Earth Science and Global Management, Euclid University, Banjul, The Gambia; E-mail: katterbauer@euclidfaculty.net*
[(b)] *Professor, Islamic Finance, Euclid University, Banjul, The Gambia; E-mail: hassan@euclidfaculty.net*
[(c)] *Distinguished Professor, Theology, Euclid University, Banjul, The Gambia; E-mail: cdk@euclidfaculty.net*
[(d)] *Professor, Islamic Finance, Yildiz Technical University, Istanbul, Turkey; E-mail: sygenc@yildiz.edu.tr*

ARTICLE INFO

Article History:

Received: 28th May 2023
Revised: 25th July 2023
Accepted: 6th October 2023
Published: 18th October 2023

Keywords:

Islamic Capital Asset Pricing Model, Shariah Compliance, Machine Learning, Chinese A-Shares

JEL Classification Codes:

K22, L11, O11, C61, C68

ABSTRACT

The CAPM makes it possible to estimate prices for specific instruments, like stocks, to project investment returns. As a key element of corporate finance and investment banking, the CAPM investigates the relationship between the level of risk associated with the investment and the inherent risks of the market as a whole. Several assumptions must be used to create the AI-driven mathematical model for Islamic financial assets to achieve the model. The first is that the expected values and standard deviations of the asset's returns are the only factors that influence investors' choices. Additionally, since the zakat and purification are deducted from the anticipated returns, there are no transaction fees. The assets may be marketable and are infinitely divisible in addition. Finally, there is no cap on the amount that may be lent or borrowed at the Sukuk profit rate or other Islamic benchmark rates because all expectations are homogenous. We presented a new AI-driven Islamic CAPM for the estimation of returns for Shariah-compliant A-Shares enterprises. The methodology represents a new AI-driven estimation framework integrated into the Islamic CAPM methodology for the estimation of returns and selection. The methodology was evaluated on an Islamic A-share portfolio, with the stocks being listed on both the Shenzhen and Shanghai stock exchanges. The analysis demonstrates the ability of the methodology to provide Shariah-compliant optimal returns for the stocks and ensure Shariah compliance of the portfolio allocations.

INTRODUCTION

The capital asset pricing model (CAPM) enables price determination for individual securities, such as stocks, to project the returns for an investment. The CAPM examines the connection between the investment's level of risk and the inherent risks of the market as a whole as a fundamental component of corporate finance and investment banking.

The CAPM enables quantifying systemic risk, which is the risk that neither a firm nor an individual can predict nor avoid. Various risks are, for example, the risk of interest rates, exchange rates, and inflation fluctuations. These are also denoted as systemic risks. There are conventionally strong correlations between the prices of assets in the market. Then a positive market trend typically implies that other assets perform reasonably well as well. This necessarily affects the systemic risk and represents a contributing factor. Risk premiums are an important part of compensation for investors to cope with systematic risk. Specifically, investors that invest in stocks with high risk, then they expect a higher risk premium or high return rate to compensate for the additional risk (Ross, 1978). The CAPM provides an approach to assisting investors with determining the expected return on investment, especially those that are riskier. This implies that many financial institutions utilize the CAPM for assessing their investments. Furthermore, they may assess whether a risky investment is worthwhile or forecast the expected performance of a portfolio. The CAPM is also frequently utilized to determine the

[1]*Corresponding author: ORCID ID: 0000-0001-5513-4418*

https://doi.org/10.46281/ijibm.v7i1.2100

To cite this article: Katterbauer, K., Syed, H., Cleenewerck, L., & Genc, S. Y. (2023). AI-DRIVEN CAPITAL ASSET PRICING MODEL FOR ENHANCING SHARIAH-COMPLIANT INVESTMENT DECISIONS – A CHINESE STOCK MARKET ANALYSIS. *International Journal of Islamic Business & Management*, *7*(1), 1-14. https://doi.org/10.46281/ijibm.v7i1.2100

weighted average cost of capital (WACC) or the financing cost of a company's assets. A critical part of this is the assessment of the cost of equity of a company (Elbannan, 2015).

LITERATURE REVIEW

The general CAPM can be represented via

$$R_a = R_{rf} + \left(B_a \times \left(R_m - R_{rf}\right)\right)$$

The parameter R_a represents the expected return on the investment, while R_{rf} is the risk-free rate of return. The parameter B_a is the beta of the investment, and R_m is the expected rate of return of the market. Finally, $R_m - R_{rf}$ is the risk premium between the market return and the risk-free rate of return. The expected rate of return represents the amount that the investor expects to earn throughout an investment. On a theoretical basis, certain securities are riskless. The risk-free rate of return in the United States is typically calculated using the yield on a three-month treasury bill or 10-year government bond. Since the US government is unlikely to default on payments, using securities issued by the government serves as the standard for risk-free rates. These assets represent no risk to investors because there have been no payment defaults (Dempsey, 2013).

A stock, asset, or investment's beta simply measures how risky it is. The beta is a numerical indicator of the stock's price volatility concerning the market. Beta can also be considered to be the stock's sensitivity to market fluctuations; a stock with a high beta will be quite volatile, whilst a stock with a low beta will not react to movements in the market as strongly. A beta of 1 indicates that the stock is similarly erratic as the market, but a beta of less than 1 indicates that the stock is more stable and less risky. Stocks with betas higher than 1 are, nonetheless, more erratic than the market. Negative betas are also possible for stocks, but they indicate an inverse link between the stock and the market. For instance, if a stock has a beta of -0.5 and the market is up 15% overall, the stock will still return -5% (Fama & French, 2004).

Whether one encounters a high or low beta depends on various circumstances. However, stocks with high beta are riskier but may be more profitable in the long run. Lower beta investments typically have lower risks but are limited in terms of returns. If stock options encounter a negative beta, then there may be various advantages or disadvantages. Based on previous data, the average amount that investors can anticipate making from investments in the market as a whole is known as the market's rate of return. The risk premium, also known as the market risk premium, in the CAPM is the discrepancy between the returns on a particular stock or investment and the risk-free rate of return (Zabarankin, Pavlikov, & Uryasev, 2014).

The CAPM has various shortcomings the CAPM, even though it is frequently utilized. First, certain questionable assumptions are made by CAPM. For instance, the formula is strictly valid only if the market is dominated by rational individuals who only consider investment returns when making decisions. The model also assumes that each market participant behaves based on the same information. Generally, there is an information discrepancy between the various actors, and they make decisions based on the individuals surrounding them (French C. W., 2003).

The usage of beta as a fundamental component of the formula is another fundamental issue with the capital asset pricing methodology. Any positive or negative variations in a stock's price are automatically interpreted by beta as signs of volatility and market sensitivity. However, the price of a stock might fluctuate for causes other than market conditions. Rather than just fluctuating randomly, stocks' prices may change deliberately (Blume & Friend, 1973).

Last but not least, CAPM exclusively uses historical data. This is a problem with a lot of financial models and one that is quite difficult to solve. The previous price fluctuations of a stock are ultimately insufficient to assess the overall risk of an investment according to the CAPM. Other factors, such as the state of the economy, the stock sector and rivals, as well as internal and external corporate actions, must be taken into account to comprehend the risk of an investment. The history behind the CAPM is extensive, but historically the theory behind risk was not well understood until the late 1960s. This may be considered unusual given that regulated insurance markets had grown highly developed by the 1700s, and stock and option markets had existed at least since 1602 when shares of the East India Company started trading in Amsterdam. Insurance companies had been using diversification to spread risk for millennia until the 1960s. The CAPM was created at a time when the theoretical underpinnings of decision-making under uncertainty were novel. These were based on empirical information about risk and return. There was generally a lack of understanding of these in the capital markets, despite the long history of actual risk-bearing and risk-sharing in organized financial markets (Muthama, Munene, & Tirimba, 2014).
Only in the 1940s and 1950s did rigorous theories of investor risk preferences and decision-making under uncertainty appear, particularly in the works of von Neumann and Morgenstern (1944) and Savage (1954). It took Harry Markowitz (1952, 1959) and Roy (1952) until the early 1950s to establish portfolio theory, which explains how investors might put together portfolios of various investments to best balance risk and return (Lestari & Silvy, 2022).

It's also worth noting that until the 1960s, when sufficient computing power became accessible, the empirical evaluation of risk and return was still in its infancy. Only then could researchers gather, store, and process market data for scientific research. Fisher and Lorie (1964) published the first thorough analysis of returns on stocks traded on the New York Stock Exchange (Lipiec, 2014).

Fisher and Lorie report average stock market return across various holding periods starting in 1926 in that paper, but they do not include the returns' standard deviation. However, they outlined that the returns of riskier assets are higher as compared to those of safer alternatives. It wasn't until Ibbotson and Sinquefield (1976) published their findings on long-

term rates of return that carefully crafted estimates of the equity risk premium were made public. They discovered that between 1926 and 1974, the Standard & Poor's 500 index's (arithmetic) average annual return was 10.9 percent, and the excess return above US Treasury bills was 8.8 percent. In their initial thorough investigation of the historical equity risk premium for UK equities, Dimson and Brealey (1978) estimated an annual rate of 9.2 percent for the years 1919 to 1977.
Before the creation of the Capital Asset Pricing Model in the 1940s and 1950s, the dominant paradigm for estimating expected returns assumed that the return investors would demand (or the "cost of capital") of an asset depended primarily on the financing method that was used to purchase the asset. Based on the proportional amounts of debt and equity financing, there was a "cost of equity capital" and a "cost of debt capital," and the weighted average of these constituted the asset's cost of capital (Lee, Cheng, & Chong, 2016).

The long-term yields of various products were used to calculate the costs of debt and equity capital. The cost of equity capital was traditionally deducted from the cash flows that investors may anticipate receiving on their shares concerning the present share price. The cost of debt capital was typically assumed to equal the rate of interest owed on the debt.

The Gordon and Shapiro (1956) model implied that a company's dividends would increase in perpetuity at a constant rate g. This was a well-liked approach to evaluating the cost of stock, as the cost of equity capital is equal to the dividend yield plus the dividend growth rate, or $r = \frac{D}{P} + g$. The dividend per share is denoted by D, and the stock price via P (Lally, 1988).

This method of calculating the cost of capital was flawed from the standpoint of contemporary finance. According to Modigliani and Miller (1958), the value of a company or an asset generally does not depend on how it is financed, at least not in a world without friction. As a result, rather than the other way around, the cost of equity capital is probably dictated by the asset's cost of capital. Furthermore, it takes a lot of judgment to estimate the cost of equity capital given projected dividend growth rates (Modigliani & Pogue, 1974).

Companies with high dividend growth rates will be evaluated by this method to have high costs of equity capital because there is no straightforward way to determine the market's prediction of the growth rate of future cash flows. The CAPM will demonstrate that there is no requirement for a relationship between the cost of capital and potential future growth rates of cash flows.

The risk was not directly factored into the cost of capital calculation under the pre-CAPM paradigm. A common working hypothesis was that a company that could finance the majority of its operations with debt was likely safe, and as a result, was thought to have a low cost of capital, whereas a company that could not support a large amount of debt was likely hazardous, and as a result, was assumed to command a high cost of capital. These general guidelines for factoring risk into discount rates were, at best, ad hoc (Chen, 2003).

The CAPM model has become of major interest to evaluate asset portfolio performance. Whether the model reflects accurately the state of the world is debatable. Second, even if the model does not accurately reflect the state of the world now, it may be able to forecast how investors will behave in the future, for example, when capital market frictions are reduced as a result of financial innovation, better regulation, and greater capital market integration. Third, the CAPM can be used as a reference point for analyzing the characteristics of the capital markets that lead to asset prices and investor actions that differ from the model's predictions (Santoso & Olilingo, 2021).

Think about the CAPM forecast that all investors will own the same (market) portfolio of hazardous assets. Investors do not own similar portfolios, which is not surprising given that taxes by themselves will lead to unique investor behaviour. Taxable investors may respond significantly differently to changes in asset values depending on when they purchased the asset, for instance, because optimal capital gains tax management entails the early realization of losses and deferral of capital gains (Constantinides, 1983).

However, if most investors own extensively diversified portfolios, it will still be a good indicator for the model. Even yet, the evidence is conflicting. On the one hand, well-known index funds allow for low-cost diversification for investors. In contrast, a large number of employees own concentrated ownership in the company through employee retirement savings plans, and a sizable number of executives own concentrated ownership in the company through stock options.

The so-called home bias in foreign investment is one of the most perplexing instances of inadequate diversification. Since international ownership of assets is generally low, investors are more likely to hold assets in their native countries.
The cost of acquiring extensive diversification in terms of taxes and direct costs can be high, and investors are prone to behavioral biases and lack of expertise, which are common defenses. If true, none of these arguments would disprove the CAPM's utility. According to the CAPM, investors who are not diversified pay a premium since they take risks for which they are not reimbursed (Fernandez V. , 2006).

As a result, there is a chance for portfolio growth, which opens doors for financial innovation and investor education. Over the past 20 years, foreign ownership of stocks has more than doubled in several nations, most likely as a result of the expanded accessibility of low-cost vehicles for international investing and the growing awareness among investors of the importance of diversification. Compared to previous decades, investors today tend to be considerably better diversified, and this trend seems set to remain (Fernandez V. P., 2005).

A crucial point to understand from the CAPM is that owning high-beta stocks does not require talent because investors can passively build a high-beta portfolio by taking a leveraged position in the market. It is far more difficult to get significant returns with low beta equities, however, as such performance cannot be duplicated with a passive strategy. Therefore, investors must evaluate performance using returns that have been suitably risk-adjusted.

According to the CAPM, the risk-free rate, the market risk premium, and the project's or company's beta vs the market are what define the appropriate discount rate for valuing predicted future cash flows of a firm or a new investment project. Since an inaccuracy in the discount rate is multiplied several times when calculating the net present value for long-dated cash flows, accuracy in predicting these parameters is crucial for making decisions in the real world (Mukherji, 2011).

Typically, historical stock market return data are used to do a linear regression study to determine beta. If there is enough high-frequency data, beta may often be reliably determined in many situations, even over a short period. It is common practice to infer beta from comparable companies whose betas can be calculated when the company or project being assessed is not publicly traded or there is no pertinent return history. When local stock market indices are employed as substitutes for the broad market portfolio because the latter is poorly described, for instance, or when the covariance with the market is time-varying, measurement problems can still occur.

The market risk premium is typically the most difficult element to measure. As opposed to variance-related indicators like beta, average returns are very sensitive to the starting and stopping levels of stock prices, and are used to determine the historical risk premium. Therefore, it is necessary to quantify the risk premium over a lengthy period. However, even this may not be enough if the risk premium changes over time.

However, none of these measurement issues directly affect the CAPM. All cash flow valuation models share a market risk premium, thus it must be estimated regardless of how challenging the process may be. Regardless of how tough it may be, beta must also be assessed if the CAPM is the "right" model (Blume & Friend, 1973).

In many ways, CAPM has been expanded. The most well-known extensions allow for heterogeneous beliefs, eliminate risk-free borrowing and lending, make some assets non-marketable, allow for multiple periods and investment opportunities that change from one period to the next, and extend to international investing. Instead, investors divide their wealth among several risky portfolios, which when combined with the wealth of all investors creates the market portfolio (Ross, 1978).

The international capital asset pricing model (ICAPM) extends to the complexities of international investment challenges. This model accounts for the fact that investors have consumption requirements unique to the nation in which they reside. British and American investors will therefore evaluate the incremental contribution that every asset contributes to portfolio risk differently, with British investors worrying about the purchasing power of the British pound and American investors worrying about the purchasing power of the American dollar. They will therefore have slightly diverse portfolios as a result. Investors simply consider one risk factor—the broader market—in the basic CAPM. Real currency fluctuations are another issue they are worried about in this globalized version of the strategy (Muthama, Munene, & Tirimba, 2014). This realization prompts the development of a model of expected returns that incorporates not only an asset's beta relative to the market as a whole but also its beta concerning currency fluctuations and any other risk that is seen differently by various investor segments.

The expected return has a multi-beta expression in almost all CAPM variations. They come from the same fundamental ideas: In equilibrium, asset prices reflect these demands; investors will hold portfolios that are optimized for their particular needs, constraints, and risk preferences; and assets with high expected returns are those that are correlated with any risk that a sizable portion of investors has been unable to eliminate from their portfolios.

It is ultimately an empirical matter as to whether the basic CAPM or one of its multifactor extensions is the "correct" model of asset prices, a topic that is covered in depth by Fama and French. Black, Jensen, and Scholes and Fama and MacBeth conducted the first tests of the CAPM, which confirmed the hypothesis by showing that high beta equities had larger returns than low beta stocks. However, the theoretical Securities Market Line did not accurately predict how strongly the relationship between beta and average returns would be (Reinganum, 1981).

Numerous studies have been conducted since this early effort to find new risk factors that influence predicted returns. The explanatory power of the CAPM is significantly improved by adding a "size" element and a "value" factor (in addition to the total market), according to Fama and French. Strong evidence that more than one systematic risk factor influences asset values can be found in the findings of follow-up research across time and nations. The value and size components, on the other hand, only serve as approximate measures of risk (French & Fama, 1996).

Size, for instance, cannot be a risk factor that influences expected returns since small businesses would then merge to become giant businesses. The fact that the Fama-French results' value effect is predicated on giving equal weight to small and large companies and is significantly stronger than that seen in capitalization-weighted value indexes is another criticism of their findings. The forecasting ability of the Fama-French model will be questioned, and the applications will be few until the risks that underpin the components are recognized. All these improvements face various challenges in that they primarily focused on the connection between interest rates and return, and utilize benchmark interest rates and fixed-income debt rates as a guide for the evaluation of the pricing of the assets. For Islamic investments, the CAPM and its various forms have to be adapted to take into account these factors.

MATERIALS AND METHODS

Machine learning has become a promising tool for enhancing asset pricing models in recent years. Large, complicated financial datasets can be analyzed using machine learning techniques since they can handle nonlinear relationships and complex data structures. Financial analysts can use machine learning to create more precise and reliable asset pricing models that consider a larger range of information, such as macroeconomic statistics, corporate fundamentals, and even news sentiment. To acquire a competitive edge in the market, machine learning is swiftly becoming a crucial tool for investors and financial institutions (Giglio, Kelly, & Xiu, 2022).

In the field of finance, machine learning has become a potent tool for enhancing asset pricing models. Financial analysts may create more precise and reliable models using machine learning algorithms that consider a larger range of inputs, such as macroeconomic statistics, corporate fundamentals, and even news sentiment. The advantages of applying machine learning to asset pricing are discussed below.

Huge amounts of data can be analyzed by machine learning algorithms to find patterns and connections that conventional asset pricing models might overlook. This may result in more accurate asset appraisals, which in turn may enable investors to make better-informed choices regarding the purchase, sale, or holding of securities (Barboza, Nunes Silva, & Augusto Fiorucci, 2023).

Large datasets can be processed and analyzed by machine learning algorithms in a matter of seconds, greatly reducing the time and effort needed by financial analysts to create asset pricing models. Financial organizations may be able to stay competitive and make quicker investment decisions with this increased speed.

A cutting-edge method for creating more precise and reliable asset pricing models is called machine learning in asset pricing. By recognizing possible dangers and forecasting market patterns, machine learning can assist financial organizations in better managing risk. Machine learning algorithms can assist financial analysts in creating more precise risk models, which in turn can assist institutions in making more informed decisions about risk management (Gu, Kelly, & Xiu, 2020).

Traditional asset pricing models cannot handle complicated data formats, such as unstructured text data, but machine learning algorithms can. This enables financial analysts to include a wider range of data sources—such as social media data, news sentiment, and other unstructured data sources—into their models. Financial organizations can dramatically lower the costs related to asset pricing by utilizing machine learning algorithms. Many asset pricing operations can be automated by machine learning algorithms, which requires less manual work and saves financial institutions both time and money.

To evaluate vast volumes of financial data, find patterns and links, and create more reliable and accurate asset pricing models, machine learning algorithms are employed in asset pricing. To create models that can effectively estimate assets, financial analysts utilize machine learning algorithms to assess a variety of data sources, such as macroeconomic statistics, corporate fundamentals, news sentiment, and social media data (Zapata & Mukhopadhyay, 2022).

Asset pricing use supervised learning algorithms to forecast asset values based on prior data. These algorithms create predictions about future asset values by using labelled data to identify patterns and connections between variables.
In asset pricing, unsupervised learning algorithms are used to evaluate huge, complicated information to find patterns and relationships that may be challenging for human analysts to spot. These algorithms can find patterns in data that were previously unnoticed and do not rely on labelled data. By learning from past data and modifying investment decisions accordingly, reinforcement learning algorithms are used in asset pricing to optimize investment strategies. These algorithms can determine the best investment plans based on historical results and current market conditions.

Large, complex information can contain links and patterns that machine learning algorithms can spot that traditional asset pricing models might not. As a result, asset appraisals are more accurate and investment decisions are better informed. The time and effort needed for financial analysts to create asset pricing models are considerably reduced by the speed at which machine learning algorithms can handle massive amounts of data. Financial institutions may better manage risk and make wiser investment decisions by using machine learning algorithms to identify possible threats and forecast market trends. Financial analysts can now include a larger variety of data sources in their models because of the ability of machine learning algorithms to handle complicated data patterns, such as unstructured text data (Goodell, Kumar, Lim, & Pattnaik, 2021).

These algorithms face a variety of difficulties. For machine learning algorithms to create reliable predictions, high-quality data is essential. Models and investment decisions may be erroneous as a result of poor data quality. Financial experts may find it difficult to comprehend how the model generated its forecasts due to the complexity of machine learning algorithms. The use of machine learning techniques can be costly, involving large expenditures on staff, technology, and software. The application of machine learning in asset pricing raises ethical questions due to the possibility of prejudice and discrimination in the model's predictions (Katterbauer K. , Syed, Cleenewerck, & Genc, 2022).

Therefore, there are many benefits to using machine learning in asset pricing, including better accuracy, faster processing, better risk management, and the capacity to handle complicated data. Implementing machine learning in finance is not without its difficulties, though, including costs, interpretability, data quality, and ethical issues.

The future prices of stocks are predicted using machine learning algorithms using historical price data and other variables. Here are a few instances of this in actual life: A machine learning algorithm created by Google's DeepMind can accurately anticipate a stock's price fluctuations up to one day in advance 86% of the time. The largest asset manager in the world, BlackRock, uses machine learning algorithms to evaluate financial data and choose which investments to make. One of the biggest hedge funds in the world, Bridgewater Associates, employs machine learning algorithms to examine massive datasets and spot market trends (Katterbauer & Moschetta, A deep learning approach to risk management modeling for Islamic microfinance, 2022).

JPMorgan Chase increases investment returns by 15% by using machine learning algorithms to enhance its investment portfolios. To optimize its investment portfolios, Goldman Sachs utilizes machine learning algorithms to scan enormous datasets and pinpoint market patterns.

By examining a lot of data and finding patterns that can forecast creditworthiness, machine learning algorithms are used to evaluate credit risk. Here are a few instances of this in actual life: LendingClub has increased loan approval rates by

40% by utilizing machine learning algorithms to evaluate credit risk and make lending choices. ZestFinance assesses credit risk for lenders using machine learning algorithms, leading to more precise and equitable loan decisions.

Machine learning in asset pricing has a bright future. Financial organizations will be able to create increasingly more precise and reliable asset pricing models as machine learning algorithms advance. The rising usage of unstructured data is one of the prospects for machine learning in asset pricing in the future. Machine learning algorithms will get better at managing unstructured data from sources like social media, news sentiment, and other sources. As a result, financial analysts will be able to use a larger variety of data sources to improve the accuracy of their asset pricing models. Additionally, deep learning will be adopted more widely (Katterbauer & Moschetta, An innovative artificial intelligence and natural language processing framework for asset price forecasting based on islamic finance: A case study of the saudi stock market, 2022).

Asset pricing will increasingly incorporate deep learning algorithms, which can learn from unstructured data. As a result, financial analysts will be able to create models that are more accurate and incorporate more variables. Reward-based learning is also being used more frequently: Asset pricing will increasingly incorporate reinforcement learning algorithms to improve investment tactics. These algorithms will allow financial organizations to choose the best investment strategies based on historical performance and current market conditions.

Improved interpretability is another key element: As machine learning algorithms grow easier to grasp, financial analysts will be able to see more clearly how the model generated its forecasts. As a result, there will be increased confidence in machine learning models, which will help financial institutions make wiser investment choices.

The increased use of explainable AI is a major element, to sum up. The usage of explainable AI, which generates models that are visible and simple to grasp, will increase in the asset pricing industry. This will assist financial institutions in adhering to rules and enhancing confidence in machine learning models. A critical part of AI development is the integration of physical models together with AI to enhance both explainability as well as the robustness of the model (Katterbauer & Moschetta, A robo-advisory framework for Islamic and Environmental, Social and Governance (ESG) compliance–A benchmark study on the S&P 500 stock index, 2022).

RESULTS

Islamic finance experiences some significant opportunities in modern finance to integrate ethical finance and financial performance to strengthen the overall financial sector. Various studies did not indicate any major differences between risk-adjusted returns based on whether they are ethical or conventional. There are various factors such as choice of benchmarks, performance measurement, ethical filters applied and investing style. Furthermore, regional considerations and economic investment horizons affect the performance of the investment portfolio.

A portfolio is mean-variance efficient if it has the highest expected return for a given variance, or if it has a negligible variance for a given expected return. Markowitz laid the groundwork in 1952 for modern investment theories. Sharpe created the CAPM for valorizing hazardous assets, building on Markowitz's prior work.

The validity of the two-parameter asset pricing theory is examined by Roll. Any reliable test requires comprehensive information on the real market portfolio's composition because of the mathematical equivalence between the individual return/"beta" linearity nexus and the mean-variance efficiency. This implies, among other things, that a proper test must encompass every individual asset. Examining inference errors caused by incomplete testing and clarifying certain ambiguities in published tests (Sadaf & Andleeb, 2014).

The development of Islamic finance raises the fundamental question of whether or not Markowitz's Mean-Variance Analysis and Capital Asset Pricing Model (CAPM), two modern investment theories and analyses, are permissible under Shariah and can be used to value Islamic financial assets. Various proponents support a separation of focus away from such models for Islamic finance purposes.

Several academics support the utilization of the Capital Asset Pricing Model for Islamic finance purposes. A risk-free interest rate, also referred to as a risk-free return, is necessary for one of the variables in the CAPM model. A risk-free interest rate is not, however, acceptable with Shariah because Islam forbids the payment or acceptance of interest charges. From a theoretical perspective, Islamic markets do not offer a risk-free interest rate.

El-Ashker creates a theoretical foundation for the conventional CAPM in asset pricing by adjusting the risk-free return to a 2.5% zakat rate. The least rate of return from assets that traders and investors would accept for bets and speculations to cover zakat and to disclose their risks is then. By omitting the risk-free return rate with the inflation rate, Hanif advises utilizing the conventional Capital Asset Pricing Model with only a small modification (Subekti & Rosadi, 2020).

To price Treasury bonds, Shaikh suggests using the classic CAPM and adjusting the risk-free return to account for the nominal GDP growth rate. However, they make theoretical and speculative assumptions about risk-free returns that are unlikely to be replicated in the financial market (Gharbi, 2016).

A major objective is the CAPM's fundamentals and the set of assumptions that underlie the model's consistency with Islamic financial principles. This requires a new mathematical methodology for pricing Islamic financial assets based on the CAPM. While there are various Shariah-compliant CAPM approaches, the challenges arising from strictly deterministic modelling make the integration of artificial intelligence essential. This may assist in the integration of Islamic financial rules and factors, which includes the ban on short-selling, purification and zakat.

The main challenge in solely applying the CAPM to Islamic finance is based on the underlying assumptions. First, there is no transaction cost and the assets are highly divisible. Additionally, there is no personal income tax and an investor cannot influence the price of a stock through his or her purchases and sales. Furthermore, investors' decisions are solely based on expected values and variance of returns and the model permits unlimited short sales. Finally, it permits unlimited lending and borrowing at a riskless rate and assumes a homogeneity of expectations. Finally, the assets are subject to the same risk (Hassan, Aliyu, Paltrinieri, & Khan, 2019).

A general model complexity reduction is that the CAPM does not assume that there are any transaction costs. The absence of costs does not conflict with any Shariah or Islamic financial standards. But it is sensible to note that when several transactions are carried out, like in permanent-time models, the addition of transaction cost results in significant deviations. The model's conclusions may be confusing or, regrettably, provide a speculative conclusion (maysir) and subject to extreme uncertainty (gharar), which would be contrary to the principles of Islamic finance.

According to the capital asset pricing model, there is no personal income tax. As there is no idea of income tax in Islam, this assumption does not conflict with any Shariah or Islamic financial principles. In contrast, Islam has the idea of zakat, a religious tax imposed only on excess wealth and not on income and applicable to all Muslims who meet the necessary asset requirements. The inclusion of zakat in the suggested modelling is therefore essential.

The infinite divisibility and marketability of the assets are presumptions made by the CAPM. In reality, it is not always possible to purchase only one unit of an asset, and investors are not always in the best possible liquidity situation. However, this supposition is designed to oversimplify the model and is in line with Shariah and Islamic finance norms.

It is important to identify all expected returns, variance, and covariance so that investors can base their decisions solely on these two factors. According to Rosly, this conforms to the Islamic tenets of al-ghunm bil ghurm (there is no reward without risk) and al-kharaj bil damam (profit comes with responsibility). The shariah maxim of "al-ghorm bil ghnom" is invoked to encourage investors to invest in ventures that involve both risk and return, such as "al-bay" (trading), "al-ijarah" (hire, lease, or rent), "salam" (forward contract) and "mudarabah" (silent partnership," where one party provides capital and the other party contributes expertise to conduct a demanding business).

Short-selling is generally not permissible in Islamic finance, and this places an important restriction on the model. Dusuki and Abozaid investigate the problem of minor sales, which include the sale of an asset that the investor does not own, clearly in violation of the bay'ma'dum (selling what the seller does not own) tenet of Islamic banking. Any income from this behaviour is seen as riba and is therefore in violation of shariah. Short selling is prohibited in Islamic finance, according to the maysir component that is present in minor sales (Hazny, Mohamad Hasim, & Yusof, 2020).

Since it resulted in a piecewise linear relationship between expected return and beta for efficient portfolios, this assumption was crucial in the development of the CAPM. According to Islamic finance, the absence of risk-free assets and the elimination of risk result from the ban on interest. However, there are instances where this supposition can be used following Shariah, such as when using Islamic financial assets that may resemble risk-free assets like sukuk (Islamic bonds). The CAPM assumes that all investors have similar expectations regarding projected returns, asset variances (risks), and asset correlation coefficients. Investors hold the same optimal portfolio if homogeneous expectations are present. Investors are urged to trade in Shariah-compliant investments in Islamic finance to generate a return (or profit) in a risky and generally recognized manner (al-ribh al-ma'ruf).

Investors should therefore be expected to assert uniform expectations in the market. Each item will therefore have a market price, which should be understood to represent the price at which investors have uniform expectations. Furthermore, according to Omar et al. (2010), shariah permits the pricing of products following market rates, which will eventually result in uniformity of expectations (Katterbauer K. , Syed, Genc, & Cleenewerck, 2023).

Since no single investor can affect the price of a stock by buying and selling, the homogeneity of anticipation indicates that investors are price takers. Investors are not allowed to manipulate prices in Islamic finance through their transactions. Investors will consistently choose the most advantageous portfolio as a result, maintaining the homogeneous expectations assumption of the classic CAPM. While the CAPM model provides some significant opportunities for Islamic finance, there are several deterministic and simplistic assumptions to derive the model that may make it not adequately applicable to Islamic assets (Sadaf & Andleeb, 2014).

To develop the AI-driven mathematical model for Islamic financial assets, several presumptions have to be utilized to attain the model. The first is that the decisions of the investors are solely dependent on the expected values and standard deviations of the returns of the asset. Furthermore, there are no transaction costs, and the zakat and purification are extracted from the expected returns. Additionally, the assets are infinitely divisible, and the assets may be marketable. Finally, all expectations are homogeneous, and there is no limit on the amount of money lent or borrowed at the Sukuk profit rate or other Islamic benchmark rates. There is a general assumption that Islamic portfolios face a diversification challenge (Hazny, Mohamad Hasim, & Yusof, 2020).

The main foundation for the model is the mean-variance optimization portfolio, where the weights of each asset are normalized such that

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

Where w_i is the weight of the asset for $i = 1, \cdots, N$. All assets are Shariah-compliant. The initial qualitative screen of the available assets represents a critical process given that this ensures that the assets are fully Shariah compliant. Shariah does not permit the investment of any assets that individually are not Shariah compliant. An advantage of such a qualitative screening is that it provides a globally universal portfolio of assets. However, the challenge is that it requires an extensive pre-screening of the assets in terms of their Shariah compliance. Given the rapidly changing environments and corporate financial conditions in terms of debt-to-equity ratios and debt-connected financial performance parameters, an AI-driven auto-filtering approach may be essential to adapt automatically to changing market conditions. For the derivation of the AI-drive CAPM, the first step is to utilize the mean-variance optimization approach. The mean-variance optimization approach is given by the multi-objective optimization problem of maximizing the return of the weighted portfolio while minimizing the variance.

$$\max_{W}(w^T r, -w^T \Sigma w)$$

s.t. $w^T \mathrm{I} = 1$

$$w \geq 0$$

The above equation implies that both the expected weighted return as well as the negative of the covariance is maximized. Because $w^T \Sigma w$ is positive definite, this implies that all values of $-w^T \Sigma w \leq 0$ for any weights. A crucial part of the adaptation of the CAPM is the integration of zakat and purification rates in the optimization routines. Both the zakat rate as well as purification rates can be considered estimated taking into account the uncertainties for the individual assets. This implies that if γ is the zakat rate, and the ρ is the purification rate, then the optimization routine can be re-written as

$$\max_{W}\left(w^T \hat{r}, -w^T \hat{\Sigma} w\right)$$
$$\text{s.t. } w^T \mathrm{I} = 1$$
$$w \geq 0$$

Where $\widehat{r_i} = (1-\gamma)(1-\rho_i) r_i, \forall i = 1, \cdots, N$, and $\widehat{\Sigma_{ij}} = (1-\gamma)(1-\rho_i)\left(1-\rho_j\right)\Sigma_{ij}, \forall i, j = 1, \cdots, N$.

The modified mean-variance optimization problem can then be transformed into the Islamic CAPM model with the same parameters represented by

$$R_k = \frac{R_s}{(1-\rho_k)} + \beta_k \left[R_M - \frac{R_s}{(1-\rho_M)}\right]$$

The resulting Islamic CAPM model is dependent on the Sukuk rate, given the assumption that the amount of money that can be borrowed or lent is not limited or subject to any other constraints. This is conventionally the case based on the fact that most Islamic funds have sufficient access to capital for investments in the form of lending and borrowing.

DISCUSSIONS

To evaluate the new Islamic CAPM framework, a solid representative portfolio of stocks is essential to have a firm comparison and analysis of the impact of the methodology on the selection of the portfolio and the returns versus risks. To determine a benchmark reference ETF, the Shariah China A-Shares ETF was launched by Value Partners Group Limited via its Malaysian subsidiary in 2021. The Shariah China A-Shares ETF utilizes a full replication strategy, where the ETF holds every constituent of the benchmark index and has almost the same weighting. The ETF is listed on the Malaysian stock exchange and enables various Shariah-compliant investors to invest in Shariah-compliant stocks. The main benefit of such A-shares investments is that it enables investors to have exposure to China's new economy, which permits participation in the country's changing dynamics and positive growth trends in the economic structure. Specifically, China has been moving towards a consumption and services-led economy, which includes companies in the technology, consumption, healthcare, and 5G space. For the screening of the Shariah methodology, the ETF utilizes a sector-based screening that excludes the sin sector companies, such as alcohol, tobacco, and gambling. Furthermore, it includes pork-related products, conventional financial services, and weapons industry, which are all excluded. The second screening methodology is quantitative that evaluates the liquidity and total debt based on the specified and approved metrics. This conventionally requires Shariah-compliant companies to have strong business fundamentals and require healthy balance sheets. The constituent of the ETF represents a base portfolio based on which other Chinese Shariah-compliant stocks were included, based on an AI-driven framework. Some selected corporations that are included in the overall A-shares portfolio are outlined in Table 1. All of these corporations are accessible via the Shanghai-Hong Kong and Shenzhen-Hong Kong stock connect, from which the data were retrieved. In total, 91 stocks were selected for the portfolio.

Table 1. Selected Chinese corporations of the Shariah-compliant portfolio.

Ticker	Name
300750. SZ	Contemporary Amperex Technology Co Ltd A SHARES (SZHK)
002594. SZ	BYD Co Ltd A SHARES (SZHK)
600900.SS	China Yangtze Power Co Ltd A SHARES (SHHK)
300760. SZ	Shenzhen Mindray Bio-Medical Electronics Co Ltd A SHARES (SZHK)
603288.SS	Foshan Haitian Flavouring & Food Co Ltd A SHARES (SHHK)
601012.SS	LONGi Green Energy Technology Co Ltd A SHARES (SHHK)
002352. SZ	SF Holding Co Ltd A SHARES (SZHK)
600276.SS	Jiangsu Hengrui Medicine Co Ltd A SHARES (SHHK)
300015. SZ	Aier Eye Hospital Group Co Ltd A SHARES (SZHK)

For the initial analysis of the overall portfolio environment in terms of their compliance, various cross-correlation analyses were conducted.

Figure 1 represents the gross margin versus operating margin for the Chinese stocks that exhibits general consistency between the data with higher gross margin implying higher operating margins. Two indicators are used to gauge a company's profitability: gross profit margin and operating profit margin. They vary in that the gross profit margin just accounts for the production's direct costs, but the operating profit margin also takes overhead into account.

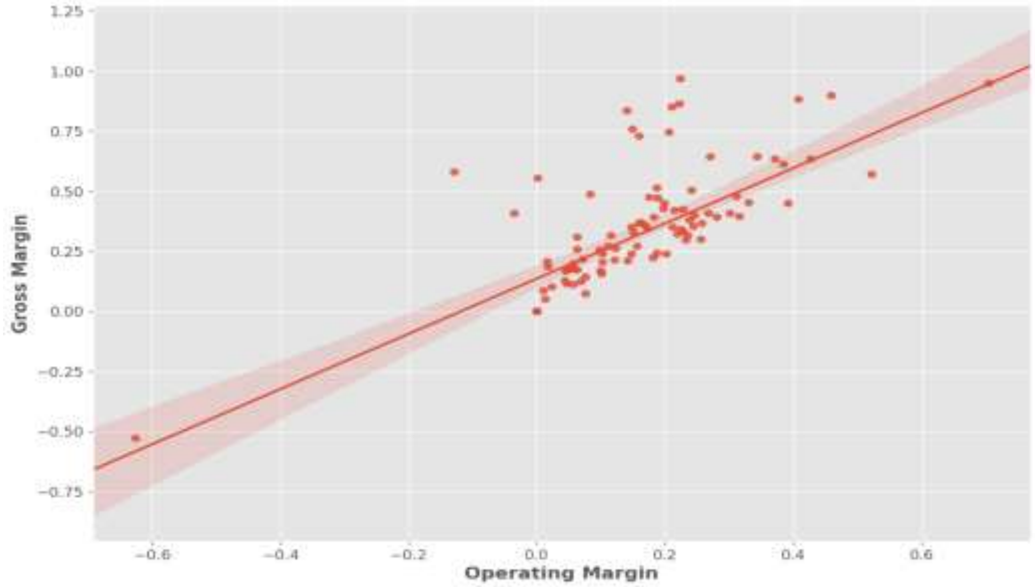

Figure 1. Gross Margin versus Operating Margin for the Chinese stocks.

Operating margin and gross margin have a lot of similarities. Both are illustrations of how effectively a business may produce a profit by quantifying it on a per-sale basis. Higher margins are preferred over those that are lower. Both may be contrasted with comparable rivals but not with companies in other industries. Companies examine their operating expenses for methods to minimize costs and attain improved efficiency to boost their profit margins since operational costs, such as payroll and advertising, offer more space for negotiation and streamlining than simple costs of production. The operational margin calculation also gives a firm a clear indication of whether it has a strong enough profit position to take on further funding to expand, as it is done without factoring in the costs of borrowing or tax charges. For investors, the operating margin is a more important bottom-line figure than the gross margin. Operating margin comparisons between businesses with comparable business models and yearly revenues are seen to be more insightful.

Because there are fewer expenses to deduct from gross income, the gross profit margin is always greater than the operating margin. Gross margin provides a more detailed look at how well a business is using the resources that are used directly in the creation of its marketable goods and services.

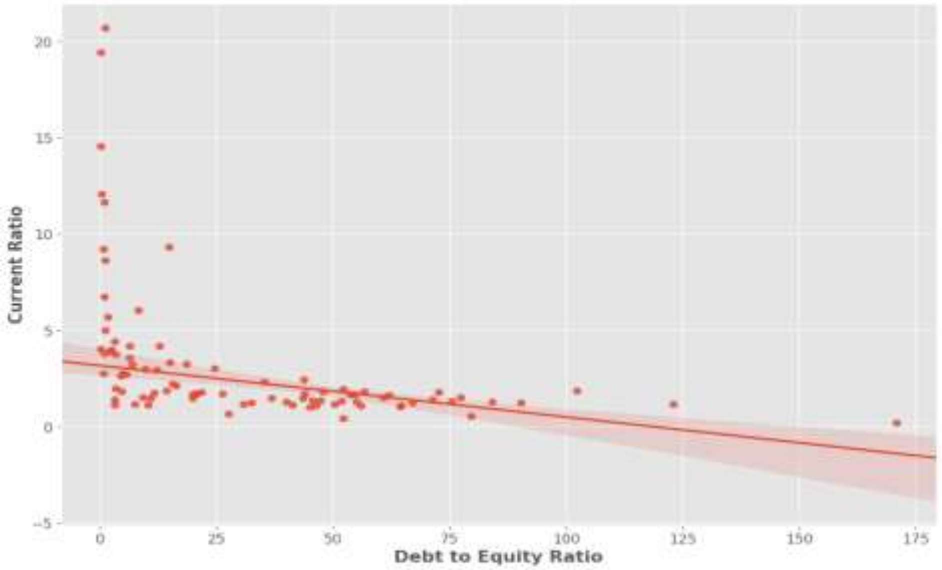

Figure 2. Current Ratio versus Debt to Equity Ratio.

The next comparison is presented in Figure 2, which represents the comparison between the current ratio and the debt-to-equity ratio. A liquidity ratio called the current ratio assesses a company's capacity to settle short-term debts or those that are due within a year. It explains to investors and analysts how a business may use its present assets to the fullest extent possible to pay down its current liabilities and other payables. In general, an appropriate current ratio is comparable to the industry norm or just a little bit higher. The likelihood of distress or default may be increased by a current ratio that is lower than the industry norm. In a similar vein, if a company's current ratio is significantly higher than that of its peer group, it suggests that management might not be making the most use of its resources.

Because it includes all current assets and current liabilities, unlike some other liquidity measures, the current ratio is named current. The working capital ratio is another name for the current ratio.

Hence, the current ratio contrasts the total current assets and liabilities of a business. Furthermore, these are often described as obligations that will be paid in a year or less and assets that are cash or will be converted into cash in a year or less. Additionally, the current ratio enables investors to compare a company's financial performance to that of its peers and rivals on an equal footing and to learn more about a company's capacity to pay down short-term debt using current assets. There is a challenge in comparing these metrics across the industrial groups, which represents a shortcoming of the existing ratio. Another challenge with the current ratios is the lack of trend information and the overgeneralization of individual asset and liabilities balances.

The debt-to-equity ratio (also known as the "risk ratio," "gearing," or "debt-equity ratio") is a leverage ratio that determines how much overall debt and financial obligations weigh against total shareholders' equity. The D/E Ratio employs total equity as a denominator as opposed to the debt-assets ratio, which uses total assets. This ratio shows the degree to which debt or equity financing dominates a company's capital structure.

When a company is steady and generating large cash flow, a greater debt-to-equity ratio suggests a levered firm, which is quite ideal, but not when a company is declining. In contrast, a smaller ratio shows a company that is less leveraged and getting closer to being completely funded by equity. Each sector has a different ideal debt-to-equity ratio.

A high debt-to-equity ratio might be advantageous since it demonstrates that a company is employing leverage to boost equity returns while also being able to easily fulfil its debt commitments (via cash flow).

We can see how employing more debt (raising the debt-to-equity ratio) boosts the company's return on equity (ROE) in the example below. Using debt instead of stock results in a smaller equity account and a greater return on equity. Increasing the D/E ratio (up to a certain degree) can reduce a firm's weighted average cost of capital (WACC) since, normally, the cost of debt is lower than the cost of equity.

In the case of a corporation with a high D/E ratio, the opposite of the aforementioned scenario is true. Any losses in this scenario will pile down, and the corporation might not be able to pay off its debt. The cost of borrowing will soar, as would the cost of equity, if the debt-to-equity ratio rises too high. The company's WACC will also soar, which will result in a decline in its share price.

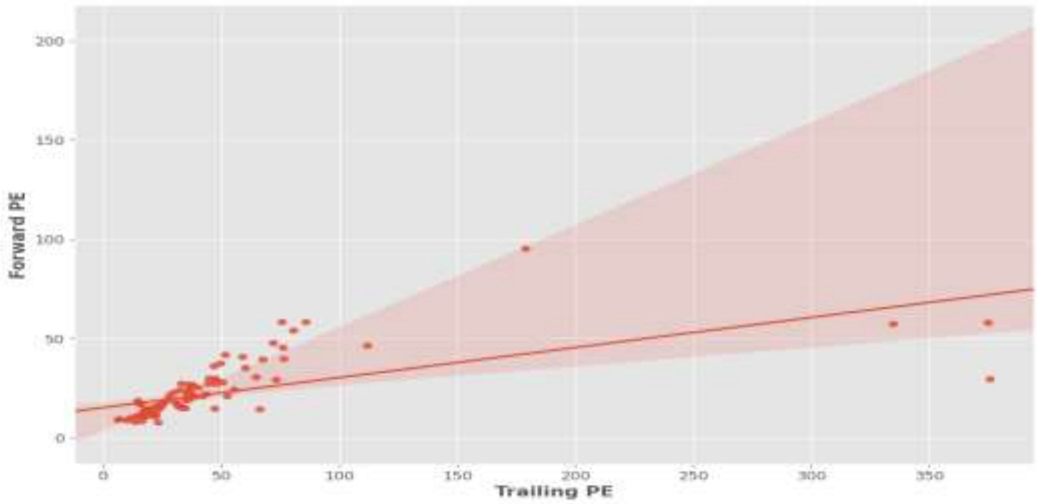

Figure 3. Comparison between the forward and trailing PE.

A key performance analysis affecting the return is the expectation towards the earnings of the corporation and the price that has to be paid. The PE ratio is the ratio of the price of the stock to the earnings per share of the corporation.

Analysts often refer to the trailing P/E when they discuss the P/E ratio. It is determined by dividing the share price (current market value) by the earnings per share for the past twelve months. Since this indicator is based on current performance rather than anticipated future performance, it is regarded as the more trustworthy of the two metrics. However, given that a company's performance elements, expenses, and profits fluctuate over time, it can turn out to be a constrained or flawed estimate. However, there are certain drawbacks to the trailing P/E, including the fact that a company's previous performance does not predict its future behaviour. Another issue is that the earnings per share figure stays the same as stock prices change.

Analysts of stocks view the trailing P/E as a kind of earnings price tag. This relative price tag can be used to find discounts or identify overpriced stocks. Some businesses should command a higher price because they have a longer track record, wider economic buffers, or several other advantages. For several reasons, some firms with a high trailing P/E ratio may be overvalued and merit lower price tags, while others may be underpriced and provide an excellent value. Analysts can compare periods year over year with the use of trailing P/E for a more precise and current assessment of relative worth. As observable from Figure 3, the enterprises exhibit generally a strong correlation between trailing PE and forward PE but generally indicate that the PE ratios in the future will be less than those of the trailing PE. This implies that the expectation is that the future returns may be less than those in the past. Taking this into account, this exhibits an important aspect that the Islamic CAPM may be able to address. Especially, risks arising from changing CAPM returns and the expected beta and sukuk rates, represent a major uncertainty factor where an AI-driven approach may be most beneficial.

For the determination of the ICAPM and the most optimal portfolio based on the maximum Sharpe ratio, the normalized asset performance over the period from July 2018 until May 2023 is visualized in Figure 4 for a selected number of stocks. The analysis indicates that the stock performance of these Shariah-compliant A-shares differ widely across the analyzed timeframe with various stocks reaching significant stock market gains, while others achieving only averaged gains.

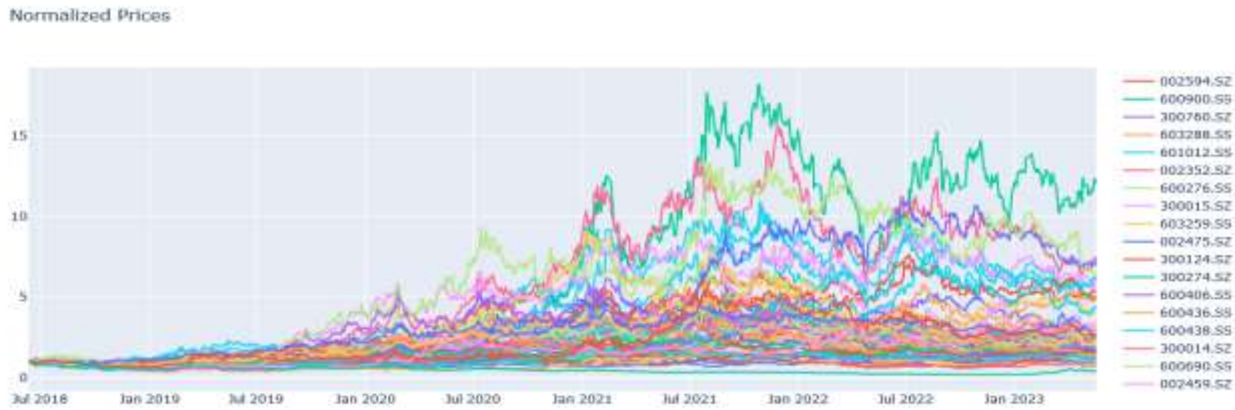

Figure 4. Normalized price development of selected Chinese A-Share stocks of the Islamic portfolio.

The collection of ideal portfolios known as the efficient frontier provides either the lowest risk or the best-projected return for a specified level of risk. Because they do not offer a sufficient return for the degree of risk, portfolios that are below the efficient frontier are not ideal. Because they have a greater degree of risk for the specified rate of return, portfolios that cluster to the right of the efficient frontier are not ideal. Portfolios (investments) are rated according to the efficient frontier on a scale of return (y-axis) vs risk (x-axis). Commonly utilized as the return component of an investment is the compound annual growth rate (CAGR), while the risk meter is represented by the standard deviation (annualized).

Graphically, portfolios that maximize returns for the taken on risk are represented by the efficient frontier. The portfolio's investment combinations will determine the returns. Risk and security's standard deviation are the same thing. A portfolio should ideally be comprised of assets that produce extraordinary returns while also having a combined standard deviation that is lower than the standard deviations of the constituent stocks. The standard deviation is lower when the securities are less synchronized (have a lower covariance). If this strategy for balancing risk and return is effective, the portfolio should align with the efficient frontier line. The concept's major discovery was the advantage of diversity brought on by the efficient frontier's curvature. The curvature is crucial in demonstrating how diversity enhances the risk/reward profile of the portfolio. It also demonstrates that the marginal return to risk is decreasing. The efficient frontier and the max Sharpe ratio are visualized in Figure 5 which indicates the average optimal spread of most of the portfolios.

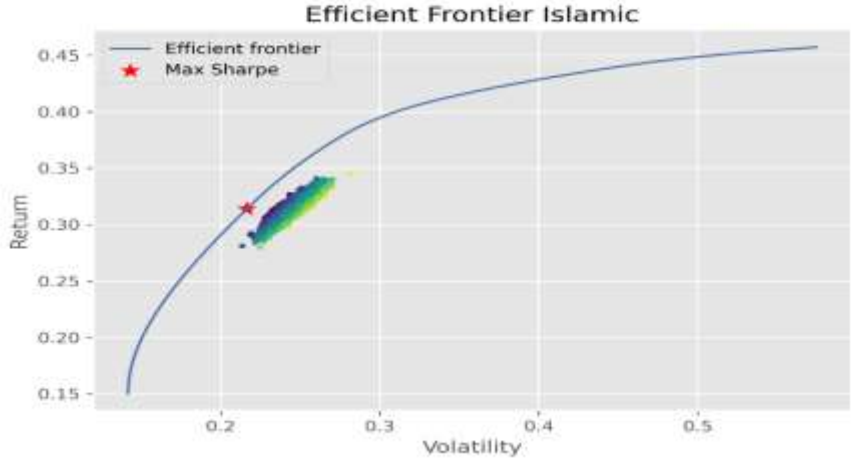

Figure 5. Efficient Frontier and max Sharpe ratio.

The optimal solution based on the Sharpe ratio was then utilized to determine the optimal portfolio weights that are displayed in Table 2, indicating a general even spread of funds amongst the various portfolio entities. An important conclusion is that the optimal solution does not require having all possible stocks to be invested in but indicates a solid spread of funds amongst the corporations. The highest-weighted corporation Imeik Technology Development (300896. SZ) has a total weight of around 14 % as part of the overall portfolio.

Table 2. Optimal Islamic portfolio weights.

Stock	Weight	Stock	Weight	Stock	Weight
300896. SZ	0.13921	002938. SZ	0.01606	603659.SS	0.0076
300999.SZ	0.11146	002603.SZ	0.01584	300759.SZ	0.00677
688396.SS	0.07874	002241.SZ	0.01513	000733.SZ	0.00582
603392.SS	0.05547	601865.SS	0.01457	300628.SZ	0.00513
603290.SS	0.04955	300751.SZ	0.0145	600176.SS	0.00471
688111.SS	0.03964	000938.SZ	0.0144	600406.SS	0.00461
600426.SS	0.0344	688008.SS	0.01399	002920.SZ	0.002
688036.SS	0.03277	002709.SZ	0.01372	300661.SZ	0.00197
601615.SS	0.03267	600196.SS	0.01289	600438.SS	0.00182
600276.SS	0.02801	600989.SS	0.01124	300274.SZ	0.00157
300763.SZ	0.02659	688012.SS	0.01065	600009.SS	0.00113
600845.SS	0.02657	603260.SS	0.00848	603833.SS	0.00102
002001.SZ	0.02169	300782.SZ	0.00845	601689.SS	0.0007
601360.SS	0.02061	600085.SS	0.00844	300450.SZ	0.00011
300433.SZ	0.02013	600547.SS	0.00796		
600900.SS	0.01936	002180.SZ	0.00791		
002050.SZ	0.0161	601100.SS	0.00786		

Finally, the Islamic alpha and beta parameters for the various stocks in the entire portfolio as compared to the optimal Islamic selection, are displayed in Figure 6. The alpha and beta estimates indicate generally limited correlation for the various stocks, which arises from the differing performance. These two important metrics for assessing the performance of a portfolio may show various correlations for the Islamic CAPM. The alpha parameter is the comparison to a market index or other wide benchmark and is a relative return. The relative volatility of an investment is measured by beta. It serves as a cue to the relative risk of the return of the stock.

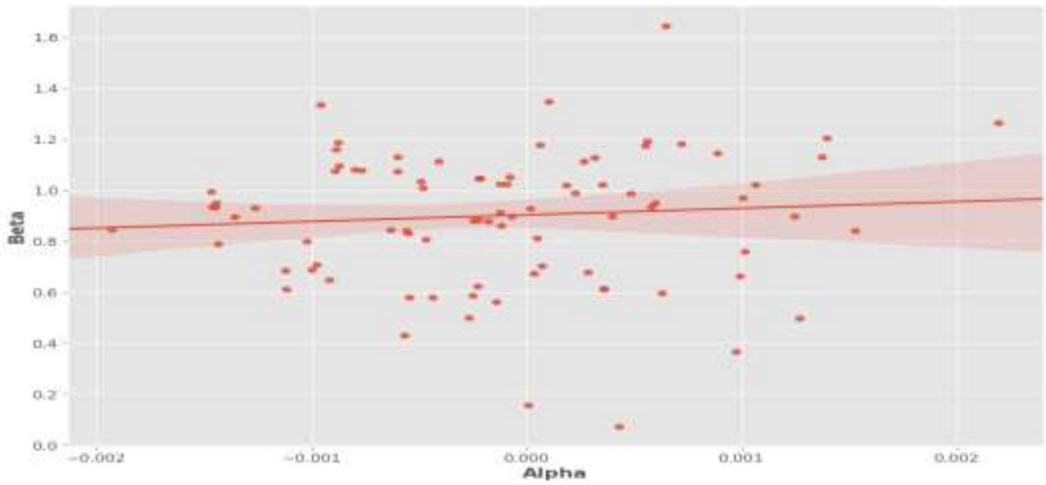

Figure 6. Comparison between alpha and beta of the Islamic CAPM.

CONCLUSIONS

The CAPM makes it possible to estimate prices for specific instruments, like stocks, to project investment returns. As a key element of corporate finance and investment banking, the CAPM investigates the relationship between the level of risk associated with the investment and the inherent risks of the market as a whole. Several assumptions must be used to create the AI-driven mathematical model for Islamic financial assets to achieve the model. The first is that the expected values and standard deviations of the asset's returns are the only factors that influence investors' choices. Additionally, since the zakat and purification are deducted from the anticipated returns, there are no transaction fees. The assets may be marketable and are infinitely divisible in addition. Finally, there is no cap on the amount that may be lent or borrowed at the Sukuk profit rate or other Islamic benchmark rates because all expectations are homogenous. We presented a new AI-driven Islamic CAPM for the estimation of returns for Shariah-compliant A-Shares enterprises. The methodology represents a new AI-driven estimation framework integrated into the Islamic CAPM methodology for the estimation of returns and selection. The methodology was evaluated on an Islamic A-share portfolio, with the stocks being listed on both the Shenzhen and Shanghai stock exchange. The analysis demonstrates the ability of the methodology to provide Shariah-compliant optimal returns for the stocks and ensure Shariah compliance of the portfolio allocations.

Author Contributions: Conceptualization, K.K., H.S., L.C. and S.Y.G.; Methodology, K.K. and H.S.; Software, K.K.; Validation, K.K., H.S., L.C. and S.Y.G.; Formal Analysis, K.K., H.S., L.C. and S.Y.G.; Investigation, K.K. and H.S.; Resources, K.K; Data Curation, K.K. and H.S.; Writing – Original Draft Preparation, K.K., H.S., L.C. and S.Y.G.; Writing – Review & Editing, K.K., H.S., L.C. and S.Y.G.; Visualization, K.K.; Supervision, K.K.; Project Administration, K.K.; Funding Acquisition, K.K., H.S., L.C. and S.Y.G.. Authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement: Ethical review and approval were waived for this study, due to that the research does not deal with vulnerable groups or sensitive issues.

Funding: The authors received direct funding for this research.

Acknowledgments: Not applicable

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

Barboza, F., Nunes Silva, G., & Augusto Fiorucci, J. (2023). A review of artificial intelligence quality in forecasting asset prices. *Journal of Forecasting, 47*(7), 1708-1728. https://doi.org/10.1002/for.2979

Blume, M. E., & Friend, I. (1973). A new look at the capital asset pricing model. *The journal of finance, 28*(1), 19-33. https://doi.org/10.2307/2978165

Chen, M. H. (2003). Risk and return: CAPM and CCAPM. *The Quarterly Review of Economics and Finance, 43*(2), 369-393. https://doi.org/10.1016/S1062-9769(02)00125-4

Dempsey, M. (2013). The capital asset pricing model (CAPM): the history of a failed revolutionary idea in finance? *Abacus, 49*, 7-23. https://doi.org/10.1111/j.1467-6281.2012.00379.x

Elbannan, M. A. (2015). The capital asset pricing model: an overview of the theory. *International Journal of Economics and Finance, 7*(1), 216-228. http://dx.doi.org/10.5539/ijef.v7n1p216

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of economic perspectives, 18*(3), 25-46. http://dx.doi.org/10.1257/0895330042162430

Fernandez, V. (2006). The CAPM and value at risk at different time-scales. *International Review of Financial Analysis, 15*(3), 203-219. https://doi.org/10.1016/j.irfa.2005.02.004

Fernandez, V. P. (2005). The international CAPM and a wavelet-based decomposition of value at risk. *Studies in Nonlinear Dynamics & Econometrics, 9*(4). https://doi.org/10.2202/1558-3708.1328

French, C. W. (2003). The Treynor capital asset pricing model. *Journal of Investment Management, 1*(2), 60-72.

French, K. R., & Fama, E. F. (1996). The CAPM is wanted, dead or alive. *The Journal of Finance, 51*(5), 1947-1958. https://doi.org/10.1111/j.1540-6261.1996.tb05233.x

Gharbi, L. (2016). A critical analysis of the use of fair value by Islamic Financial Institutions. *Journal of Islamic Accounting and Business Research, 7*(2), 170-183. https://doi.org/10.1108/JIABR-10-2013-0037

Giglio, S., Kelly, B., & Xiu, D. (2022). Factor models, machine learning, and asset pricing. *Annual Review of Financial Economics, 14*, 337-368. https://doi.org/10.1146/annurev-financial-101521-104735

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance, 32*, 100577. https://doi.org/10.1016/j.jbef.2021.100577

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223-2273. https://doi.org/10.1093/rfs/hhaa009

Hassan, M. K., Aliyu, S., Paltrinieri, A., & Khan, A. (2019). A review of Islamic investment literature. *Economic Papers: A journal of applied economics and policy, 38*(4), 345-380. https://doi.org/10.1111/1759-3441.12230

Hazny, M. H., Mohamad Hasim, H., & Yusof, A. Y. (2020). Mathematical modelling of a shariah-compliant capital asset pricing model. *Journal of Islamic Accounting and Business Research, 11*(1), 90-109. https://doi.org/10.1108/JIABR-07-2016-0083

Katterbauer, K., & Moschetta, P. (2022). A deep learning approach to risk management modeling for Islamic microfinance. *European Journal of Islamic Finance, 9*(2), 35-43. https://doi.org/10.13135/2421-2172/6202

Katterbauer, K., & Moschetta, P. (2022). A robo-advisory framework for Islamic and Environmental, Social and Governance (ESG) compliance–A benchmark study on the S&P 500 stock index. *The Journal of Muamalat and Islamic Finance Research, 19*(1), 34-46. https://doi.org/10.33102/jmifr.v19i1.408

Katterbauer, K., & Moschetta, P. (2022). An innovative artificial intelligence and natural language processing framework for asset price forecasting based on islamic finance: A case study of the saudi stock market. *Econometric Research in Finance, 6*(2), 183-196. https://doi.org/10.2478/erfin-2021-0009

Katterbauer, K., Syed, H., Cleenewerck, L., & Genc, S. Y. (2022). Robo-Sukuk pricing for Chinese equities. *Borsa Istanbul Review, 22*(5), 854-860. https://doi.org/10.1016/j.bir.2022.06.002

Katterbauer, K., Syed, H., Genc, S. Y., & Cleenewerck, L. (2023). Integrating Islamic Principles of Taxation within China–An Analysis of its Impact on Corporate Earnings. *JOEEP: Journal of Emerging Economies and Policy, 8*(1), 104-110.

Lally, M. (1988). The Gordon-Shapiro Dividend Growth Formula and Inflation. *Accounting & Finance, 28*(2), 45-51. https://doi.org/10.1111/j.1467-629X.1988.tb00144.x

Lee, H. S., Cheng, F. F., & Chong, S. C. (2016). Markowitz portfolio theory and capital asset pricing model for Kuala Lumpur stock exchange: A case revisited. *International Journal of Economics and Financial Issues, 6*(3), 59-65.

Lipiec, J. (2014). Capital Asset Pricing Model Testing at Warsaw Stock Exchange: Are Family Businesses the Remedy for Economic Recessions? *International Journal of Financial Studies, 2*(3), 266-279. https://doi.org/10.3390/ijfs2030266

Modigliani, F., & Pogue, G. A. (1974). An introduction to risk and return: Concepts and evidence, part two. *Financial Analysts Journal, 30*(3), 69-86.

Mukherji, S. (2011). The capital asset pricing model's risk-free rate. *The International Journal of Business and Finance Research*, *5*(2), 75-83.

Muthama, A. K., Munene, M. G., & Tirimba, O. I. (2014). Empirical tests of capital asset pricing model and its testability for validity verses invalidity. *International Journal of Innovation and Applied Studies*, *9*(2), 600.

Reinganum, M. R. (1981). A new empirical perspective on the CAPM. *Journal of financial and quantitative analysis, 16*(4), 439-462. https://doi.org/10.2307/2330365

Ross, S. A. (1978). The current status of the capital asset pricing model (CAPM). *The Journal of Finance*, *33*(3), 885-901. https://doi.org/10.2307/2326486

Sadaf, R., & Andleeb, S. (2014). Islamic capital asset pricing model (ICAPM). *Journal of Islamic Banking and Finance, 2*(1), 187-195.

Subekti, R., & Rosadi, D. (2020, July). Modified capital asset pricing model (CAPM) into sharia framework. In *Journal of Physics: Conference Series* (Vol. 1581, No. 1, p. 012021). IOP Publishing. https://doi.org/10.1088/1742-6596/1581/1/012021

Zabarankin, M., Pavlikov, K., & Uryasev, S. (2014). Capital asset pricing model (CAPM) with drawdown measure. *European Journal of Operational Research, 234*(2), 508-517. https://doi.org/10.1016/j.ejor.2013.03.024

Zapata, H. O., & Mukhopadhyay, S. (2022). A Bibliometric Analysis of Machine Learning Econometrics in Asset Pricing. *Journal of Risk and Financial Management, 15*(11), 535. https://doi.org/10.3390/jrfm15110535