Unlocking Market Insights and AI-Driven Stock Return Analysis of the KMI-30 Index

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Abstract

Monitoring and assessing market risks is becoming crucial now-a-days for investors, financial institutions, authorities, and other parties. This study examines several models considering the business risk metric Value at Risk (VaR) to determine the optimal framework for the KMI-30 stock market. In this study, we have investigated the potential of artificial intelligence (AI) in assisting investors to navigate the highly volatile stock markets and minimize financial Risk. Our analysis focuses on the KMI-30 index, utilizing a comprehensive dataset spanning the past decade, from January 2012 to December 2022. To facilitate our research, the researcher initially organized the data in Excel and imported it into STATA, where AI-driven algorithms were employed to calculate investment returns. The researcher implemented the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to enhance our risk assessment with parameters set at 1,1. It allowed us to estimate the Value at Risk (VAR) and gain valuable insights into market dynamics and risk exposure. Our findings demonstrate the efficacy of AI in rapidly processing and analyzing large volumes of financial data, enabling investors to make informed decisions promptly. Researchers have observed that investors can significantly improve their decision-making processes by correctly utilizing AI methods. The results underscore the potential for AI to enhance decision-making in the financial world, particularly in volatile stock markets. This study contributes to a growing body of research highlighting the practical utility of AI in finance and its potential to mitigate financial risks for investors, ultimately leading to more informed and profitable investment strategies.

Keywords: VaR, ARCH, GARCH, Volatility, KMI-30.

Introduction

Discussions on how to keep people at the base of the economic pyramid economically active are giving increased attention to the role of financial technology inclusion (Peric, 2015). Banks and non-bank organizations work together to use digital financial methods to reach underserved and underbanked populations (Peric, 2015). For years, digital approaches have been used by banks and non-banking companies alike to increase access to people who previously held positions at traditional banks (Alameda, 2020; Peric, 2015). By way of the third industrial revolution's paper and physical cash circulation, the fourth technological advancement entered the staid banking business (Alameda, 2020). "Financial technologies," or "fintech" for short (Mamoshina et al., 2018), refer to innovative methods of doing business with the potential to alter the financial services sector significantly. The financial technology business model is based on the wide utilization of the Internet to offer different financial services or products in an automated way (Paul, 2019). A.I., machine learning, advanced analytics, and public blockchain technologies are all part of Industry 4.0. They can help new fintech and traditional companies stay ahead (Lopes &

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Pereira, 2019a). The audio production process, knowledge representation, speech-to-text, learning techniques, expert systems, language processing, deep learning (ML), robotic systems, and symbolic logic are some other A.I. techniques that can be used in the fintech sector to help people get access to money (Paul, 2019). Many consider 2011 the tipping point when major tech companies like Microsoft, IBM, and F.B. began pouring resources into developing artificial intelligence and machine learning applications for business.

Some customers of traditional banks may be worth billions of U.S. dollars since they have been with the bank for hundreds of years (Alameda, 2020; Peric, 2015). However, these customers need to be digital, which is problematic (Alameda, 2020; Loufield et al., 2018). However, despite the wealth of digital insight available to new entrants in the financial technology sector, gaining customers' trust remains a significant challenge (World Bank, 2020). Customers got a new look at fintech when COVID-19 caused problems because it was the only way to do banking and shopping. Banks used digital banking, while people in many countries shopped online and used different banking apps to make transactions. Also, tech companies like Google, Apple, Facebook, and Amazon in the U.S. and Baidu, Alibaba, and Tencent in Asia, which are proud to have millions of customers, investment rewards in the billions, and centuries of heritage, and a pure digital vision, will show banks how to use digital technology and how important A.I. is in finance (Alameda, 2020). According to the World Bank, more than eighty countries now offer some form of digital financial service accessible through mobile devices (Chu, 2018). Therefore, millions of hitherto excluded and underserved poor people are moving from money interactions to formal financial services, where they have access to a wider range of services, including payments, remittances, credit, insurance, securities, and savings (The World Bank, 2020). The widespread adoption of mobile phones and other digital technologies, like AI, and the resulting increase in the number of people with access to formal financial services is encouraging (Salampasis & Mention, 2018; Bill & Melinda Gates Foundation, 2019). Customer-friendly, economically viable, and low-priced financial services are made available to digitally connected consumers through digital financial inclusion (Gomber et al., 2017). Although non-financial companies' involvement in the provision of new technology employed in providing digital financial services presents many hazards, the rewards to previously excluded customers are limitless (The World Bank, 2020; Rathi, 2016). Artificial intelligence, as proposed by (Hassani et al., 2020), can be understood in various ways. Because of this, AI cannot be defined by a single term (Hassani et al., 2020). Legg and Hutter (2007) provided 70 definitions of AI that encompassed various perspectives. Colom et al. (2010) and Snyderman and Rothman (1987) characterized artificial intelligence as the capacity for generalized reasoning, problem-solving, and learning. Gottfredson (1997) provided another definition of A.I., emphasizing quick learning and experience-based adaptation. The term "artificial intelligence" (AI) was coined by (Hassani et al., 2020) to describe a system designed to collect, store, and analyze data and to carry out specific activities without human intervention. A.I. has a significant capacity to establish a base for decision-making and assistance through insights and outcomes obtained from enormous and complicated data sets that are condensed into a controllable size (Hassani et al., 2020).

Generations of mathematicians, philosophers, and scientists had been mulling over the concept of artificial intelligence by the 1950s (Editorial with 52 Researchers, 1994). Stories and tales of artificial beings endowed with cognition or awareness by master artists during the various epochs of human classical culture (Gottfredson, 1997) are said to be the first examples of artificial intelligence. Classical thinkers' attempts to reduce human thought to converting natural symbols lent further depth to artificial intelligence (Colom et al., 2010). The introduction of programmed computer systems in the 1940s marked the culmination of an endeavor to characterize human thought as mechanical manipulation, as Colom et al. (2010) explained. These digital computers were built on the logical foundations of mathematics (Hassani et al., 2020). The thoughts around the produced gadget prompted some scientists to start contemplating, with seriousness, the prospect of trying to come up with an artificial brain (Gottfredson, 1997). The main objective of this thesis is to calculate the VaR model through Stata using the KMI-30 index. This study will highlight how investors can get help through AI to minimize the Risk. As financial risk modeling gained popularity, there has been much research on VaR and related methodologies. VaR modeling has been studied since at least 1995, when (Beder, 1995) analyzed eight of the greatest used VaR models. Beder concluded that model design and fundamental presumptions play a substantial role in the outcome because his research showed that for the portfolio, which was the same, the VaR calculations varied dramatically amongst models.

VaR for many stock series and the OMX indicator of the Stockholm Stock Exchange is estimated by (Nasser, 2003) using many generalized conditional autoregressive heteroskedasticity (GARCH), proposed by Engle (1982). Among his findings is the conclusion that the GARCH method (1, 1) conventional model is adequate for determining VaR. To determine the best VaR model, Schmidt and Duda (2009) combed through many parametric and non-parametric approaches used on three indicators for their master's thesis. While the Conditional Autoregressive VaR (CAViaR) presented by Engle and Manganelli (2004) performed the best in their backtesting study based on 250 observations, it was shown to be less exact when estimating 1-day 99% VaR. They also discovered that using a GARCH (1, 1) model to model volatility improves estimates. Investors, traders, and analysts all look to the KMI-30 index to get a sense of the health of the Pakistani stock market. Thus, any methods that can reduce financial Risk in the index could have far-reaching effects on the market's overall health. Second, artificial intelligence (AI) is becoming increasingly popular in the financial sector, and this has the possibility of drastically altering how banks and investors deal with Risk. The real-time analysis, pattern recognition, and prediction capabilities of A.I. algorithms applied to enormous amounts of financial data can inform investment plans and risk management methods. AI makes it feasible to reduce investment risk in the KMI-30 index more efficiently and effectively than before. Finally, the proposed study is important because it will provide much-needed insight into the advantages and disadvantages of employing A.I. in this capacity in developing economies like Pakistan. The United States and Europe have been at the forefront of AI research. However, there may be discrepancies in the applicability of AI in emerging nations due to disparities in available data, regulatory frameworks, and investing culture. This study has the potential to highlight the viability and effectiveness of A.I. in developing market environments by studying its usage for managing financial risks in the KMI-30 index.

Literature Review

The correlation between shifts in oil prices and GDP growth in Nigeria has been the subject of numerous academic studies. (Asaola & Ilo, 2012) looked at the relationship between the value of the Nigerian stock market and the cost of crude oil around the world. Given the outsized effect of the oil business on the Nigerian economy, the analysis discovered long-term linkages between the Nigerian stock market and oil prices. Ogiri et al. (2013) examined the correlation between oil prices and Nigeria's performance in the stock market using VECM and VAR models. Their research indicates that oil price swings are a major factor in Nigerian stock market volatility. Akinlo (2014) investigated the link between the price of oil and the Nigerian stock market using the Vector Error Correction Model technique. The findings suggest a short-term, positive effect of oil prices on stock market growth in the country and show that oil prices, the exchange rate, and the stock marketplace growth are all cointegrated. Using GMM and time series data collected annually from 1981 to 2012, Alley et al. (2014) investigated the effects of oil price shocks on the Nigerian economy in greater depth. They found that unexpected increases in oil prices minimally slowed economic development, while the price had a significant positive effect. Twenty nations in Sub-Saharan Africa were studied by Akinlo and Apanisile (2015) to determine the impact of oil price fluctuations on economic growth between 1986 and 2012. Using a group of pooling OLS, researchers discover that fluctuations in oil prices benefit the economies of countries that export petroleum but have no effect on the economies of non-oil exporting nations.

Using daily, monthly, and quarterly data sets, Abdulkareem and Abdulkareem (2016) evaluated economic indicators and volatility in oil prices in Nigeria using the GARCH model and its modifications. Odupitan (2017) found that a fall in government income and a contraction in the non-oil sector were both caused by the global crash in crude oil prices in 2014, supporting the study's conclusion that the price of oil is a significant source of market volatility in Nigeria. The economy of Nigeria suffered as a result, with jobs lost, savings rates remaining unchanged, and the country's external debt rising. Odupitan argued that the Nigerian government should consider and implement economic diversification to solve these difficulties. Jarrett et al. (2017) used the ARDL model to analyze the effects of local economic literacy and openness on reducing oil price volatility using a dataset of 194 countries from 1980 to 2014. They concluded that there are ways to lessen the blow of oil price swings and that doing so would require only minor adjustments to the financial system. Using the ARDL model, Okere and Ndubuisi (2017) looked into the correlation between the price of crude oil, the growth of the stock market, and GDP expansion in Nigeria from 1981 to 2014. The study found that the high oil price is a major factor in the country's rising standard of living.

The SVAR-GARCH model was used by Ahmadi & al., (2018) to investigate the connection between expenditure and uncertainties in the U.S. oil and gas sector. They discovered that uncertainty in the oil market harms financial investments with a one-year lag and that this effect is driven solely by consumer spending demand shocks. Finally, Okoye et al. (2018) empirically analyzed the linkages between Nigeria's construction industry, oil prices, and GDP, discovering short-run linear connections between macroeconomic variables. They claimed that the economy as a whole was unaffected by fluctuations in the building industry or oil prices.

However, in Nigeria, investors frequently consider the stock's performance before committing capital. Therefore, this study aims to examine the effectiveness of Total Nigeria Plc stock returns systematically. The researcher also empirically grounded our research with Value at Risk (VaR). VaR is a quantitative metric used to evaluate the danger of a financial firm or a collection of commodities (Corkalo, 2011). Maximum loss during a certain time, in terms of a specific currency or stock price, at a specified level of certainty (Best 1998; Bali & Cakici, 2004). VaR has become widely used as a measure of market risk by financial institutions such as banks, trading firms, and non-financial businesses like Total Nigeria Plc (Tripathi & Aggarwal, 2008). Okpara (2015) used the VaR technique to assess the vulnerability of the Nigerian stock market. The EGARCH model with an individual's t innovation distribution could offer a more precise estimate of VaR, as found by Okpara (2015), who found that traders and investors in Nigeria's stock market hold long positions in trades according to the Akaike information criteria (AIC).

Instead, they evaluated danger based on the deviation of realized returns (R) from forecasts. In addition, Bali and Cakici (2004) argued that VaR and the stock size and liquidity can describe the longitudinal variance in returns above and beyond beta and total volatility. They concluded that the correlation between average results and VaR is robust across time horizons and loss thresholds, with VaR providing additional explanatory power to stock market returns.

Corkalo (2011) applied variance-covariance, historical simulation, and bootstrapping procedures to stock portfolios to compare the most common approaches to calculating VaR and displayed the results using a histogram. Before settling on a VaR calculation approach, they advised traders of risk managers to take stock of their portfolio's composition. However, more written content on VaR's application to Nigerian stocks needs to be written. Global Innovation Exchange (2019) used the VaR model to compare the risk profiles of the Nigerian Stock Exchange (NSE) to the Stock Exchange of Johannesburg (JSE). At the same time, NSE VaR returns daily between 2008 and 2014. reached its highest point in 2009, and JSE VaR reached its highest point in 2008. The outcomes lined up with what would be predicted by standard market behavior. Oduwole (2015) used the minimal conditional Risk of value (MCVaR), which is related to the VaR technique, to study the performance of Nigerian mutual funds from 2011 to 2014. According to the results, between December 2012 and November 2014, the MCVaR strategy had better returns than both the mutual funds and the index of the Nigerian Stock Exchange. The research of Nwude (2013) and the SEC provides insight into other types of market risk, such as the assessment of equity risk premiums in Nigeria (2019).

Most studies use the GARCH model to predict Bitcoin's Value at Risk, but some also factor in the value of other cryptocurrencies, equities, and even global currencies (2016). As of this writing, Ardia et al., Liu et al. (2020) Trucios (2019). VaR estimate in the cryptocurrency market has been studied by the following researchers using the GARCH family and the fundamental benchmark model (Bouoiyou & Selmi (2014); Nieto et al., E. (2016) Bouri et al. (2019a) studies by Delfin-Vidal et al. (2016), Katsiampa (2017), Peng et al. (2018), Ardia& Hoogerheide (2019). For instance, Peng et al. (2018) examine the efficacy of the symmetric Gaussian, asymmetric Student t, and generalized augmented GARCH (SVRGARCH) models. To predict volatility in the bitcoin market, support vector regression GARCH was shown to be superior to GJRGARCH. To better understand the volatility of bitcoin returns, Dilek Teker and Suat Teker (2020) tried several different models, including ARCH, GARCH, TGARCH, and EGARCH. The empirical findings reveal that the GARCH (1,1) model best explains the volatility of Bitcoin returns for the data set that was utilized for the study. Bitcoin price volatility was also calculated by Katsiampa (2017), who found that AR (1) -CGARCH provided the most accurate estimates based on empirical data. Liu et al. also used an NRIG model with a normal distribution based on t error under GARCH to assess the volatility of Bitcoin returns. The results show that GARCH with a Student t distribution is the best-performing model. The scope of other research expanded to incorporate a wider variety of monetary resources. In a study estimating Bitcoin, Gold, and U.S. Dollars volatility, Dyhrberg (2016) found that the GARCH and asymmetrical E-GARCH models react similarly and are best suited for hedging. Both Bouoiyour and Selmi (2015) and Dyhrberg (2016) found that bad news tends to strongly increase volatility in contrast to positive news, revealing that Bitcoin volatility follows a similar pattern. However, a study done by Dyhrberg (2016) utilizing asymmetric GARCH found that Bitcoin might be highly effective in the risk management of risk-averse investors who tend to act on unfavorable news in the market. By utilizing many GARCH models, Bouoiyour and Selmi (2019) investigated Bitcoin's price volatility. They split the data collection time in half (Dec 2010–June 2015 and January 2015–June 2015). One set of findings showed that persistent volatility could be evidenced using an estimated Threshold GARCH model. In contrast, another set showed that persistent volatility could be reduced by using a fitted Exponential

GARCH model. The literature suggests a need to check the KMI-30 Index stock returns to minimize the Risk for investors through an AI approach.

Theoretical Model

Value at Risk, often VaR, is a financial risk measurement used to determine the greatest loss that might be incurred with a specific probability over a specified time horizon. Let's use an example to demonstrate this. Consider a company's daily annual losses and profits (P/L). The bell-shaped curve shown in Figure 3.1 is likely the result of plotting these P/L data in a histogram. Researchers can observe that relatively few days have large losses or gains, while most days have returned close to zero. If the researcher was interested in the 95% VaR for one day, the researcher would cut somewhere between the lowest 5% and the highest 95% of the data. Take note of the VaR's positive sign, which represents a loss of that value. To compute VaR, the researcher must always mention two things:

• A holding or perspective period is the time frame used to calculate a portfolio's profit or loss. Although it can also be weekly or monthly, this typically has a 1-day to 10-day horizon.

• A confidence level will indicate the likelihood that the researcher will not suffer a loss worse than our VaR. The confidence level can be assigned any proportion between 0 and 1 but is frequently set to 95% or 99%.

Moreover, VaR may be stated for short and long positions-1 if the researcher wishes to predict the Risk associated with a financial condition for the following k periods at time t. Let the cumulative distribution function (CDF) of V(k) equal F(k) and have V(k) reflect the change in location value from one-time t to another time t + k and a level of confidence (x). VaR for a single long position is therefore.

1 = P r[V (k) V aR] = Fk (V aR), where P r[V (k) V aR] = 1 = 1 P r[V (k) V aR] = 1 Fk (V aR). (3.2)

Note that the right tail of Fk(x) is interesting for a short position and often has a positive valuation. In contrast, the left tail is interesting for a long position and often represents a negative valuation (Tsay, 2005). VaR will always be a positive figure reflecting a loss in the allocation's left tail; the researcher will not discuss the position further in this thesis. Instead, we will focus on P/L in terms of index returns. VaR has limitations, even if it is a helpful instrument for calculating and monitoring market risk. First, VaR is frequently criticized for not predicting the greatest possible loss, i.e., how much more cash an investor can lose than our VaR. The need for the in-sample period chosen to accurately reflect the future, an assumption that may only sometimes apply, is another disadvantage of quantifying historical VaR (Jorion, 2009).

Moreover, Dowd (2013) emphasizes the Risk of relying on VaR because the metric is typically too harsh to reflect all the hazards. VaR will vary from model based on the framework and assumptions the researcher uses, increasing the metric's uncertainty. According to Taleb (1997), relying on false information is worse than not knowing at all. A pilot will crash the aircraft if the researcher gives him an altimeter that occasionally has a problem. Throughout the years, several techniques for modeling VaR have been put forth. Investors shall restrict themselves to comparing five models in this thesis. The first two are the Age-Weighted Historical Simulations (AWHS) and the Basic Historical Simulations (H.S.). These models make no assumptions regarding the a priori distribution of returns. Volatility-weighted HS (VWHS) is the third model that uses a GARCH model to predict volatility. Variations on the t-distribution, the standard distribution, and the skew t-distribution will be used to disperse the innovations in the unknown equations. The latter two models suppose normal and t distributions, respectively, for log returns. When discussing returns (r), the researcher will henceforth always use the daily data as the log (Vt Vt1), where Vt represents the score of the OMXS indices at time t (or the closing price of Boliden) and Vt1 is the score of the OMXS indices at time t (or the closing price of Boliden) the day before. VaR consumers, such as banks, must evaluate risks not in terms of log returns but in consideration of basic P/L and returns. Since this thesis relies on historical data to select the most effective VaR model, the small number of observations and easy method of converting log returns to the original form is of little consequence. Log returns, hereafter indicated by r, will be used instead.

Methodology

The KMI-30 index daily closing prices are taken from the investing.com website and organized in Excel. The data range was from 2012 to 2022. Data was imported to STATA for further analysis. For calculating VAR, the researcher calculated the daily returns of stock prices and then GARCH 1,1. The ten years of the datasets, January 2012 to 30th December 2022, containing 132 observations, are used to estimate VaR for the following day, January 2023. The choice of the GARCH (1,1) model is grounded in its ability to capture the time-varying volatility inherent in financial data. Financial markets exhibit periods of high and low volatility, and the GARCH model provides a robust framework for modeling these variations. The "1,1" specification indicates that the model considers the first-order autoregressive term for conditional variance and the first-order moving average term for conditional error variance, consistent with empirical observations of financial data. Stock returns exhibit volatility clustering, where periods of high volatility tend to cluster together. ARCH (1,1) effectively accounts for this phenomenon by allowing conditional volatility to depend on past squared returns and past conditional variances. It reflects that further extreme movements often follow extreme market movements. ARCH models, including ARCH (1,1), have been widely adopted in empirical finance due to their demonstrated success in modeling financial time series data. They have been extensively tested and applied in various financial contexts, making them a credible choice for calculating stock returns.

The estimation of VAR has been done in STATA while applying the following AI coding.

$gen\ ri = ln(closing/closing[\_n-1])$…..... (1)

$gen\ mofd\ =\ mofd(date)$………. (2)

$format\ of\ \%tm$

Equation 1 is for the daily returns however, for the monthly returns we used Equation 2. The above code is used for calculating the monthly returns of the Karachi Meezan index. After the returns, the next step is to calculate the value at risk which has been done through the following codes in STATA.

$arch\ y\ x, arch(1{,}2)\ March(2)$……... *(3)*

Equation 3 is for calculating the Garch and Arch model, but it has to be changed according to the variable. VaR, or "value at risk," is a financial measure of the risk that estimates the worst-case scenario for a certain investment over a specified time horizon. Let us use an example to see how this works. Let us pretend we have the company's daily P/L for a year. A bell-like shape distribution, such as the one shown in Figure 1, would likely result from plotting all P/L in a histogram. We can observe that most days' results are close to zero, with only a handful showing severe losses or gains. We may examine the 95% VaR for one day by drawing a line between the lowest 5 percent and the highest 95 percent of data. During this time, the 1-day 95% VaR is 1.645, corresponding to the number -1.645 in figure below, a typical normal distribution. Pay attention to VaR's positive sign, which indicates a loss of 1.645.

Table 1

File Edit View Data Tools

closing[1] 21658.551

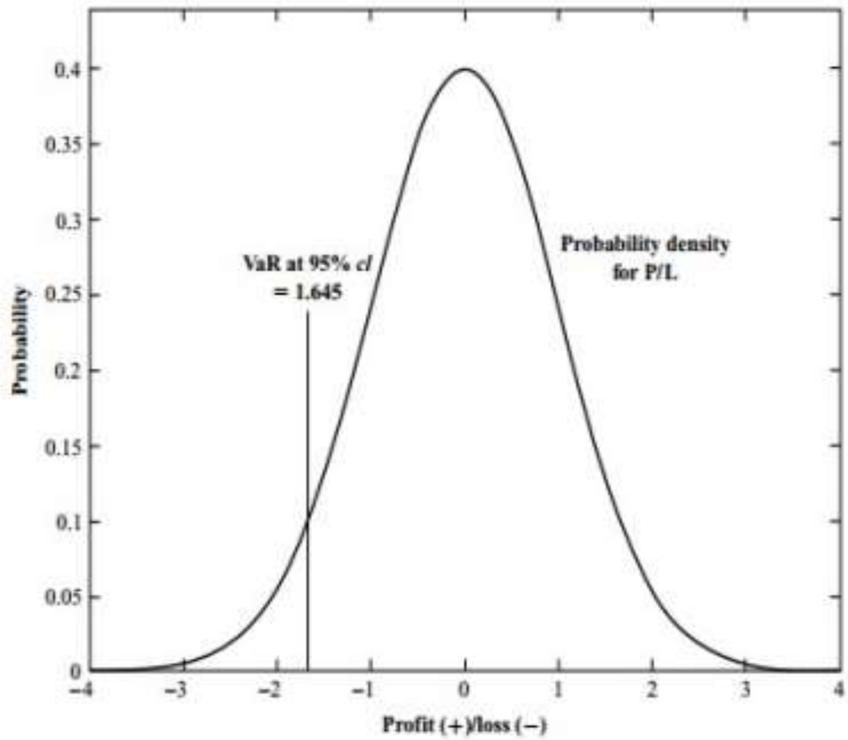
	closing	date	stock_return	months
1	21658.6	2012-01-01	-.742746	2012m1
2	20108.2	2012-02-01	-.0742746	2012m2
3	21658.6	2012-03-01	.0742746	2012m3
4	22903.3	2012-04-01	.0558816	2012m4
5	23553.7	2012-05-01	.0279998	2012m5
6	24248.4	2012-06-01	.029069	2012m6
7	24002.9	2012-07-01	-.010176	2012m7
8	23813.5	2012-08-01	-.0079216	2012m8
9	25135.2	2012-09-01	.054015	2012m9
10	27244.5	2012-10-01	.0805822	2012m10
11	27478.2	2012-11-01	.0085431	2012m11
12	27818.2	2012-12-01	.0122986	2012m12
13	28532.4	2013-01-01	.0253497	2013m1
14	29134	2013-02-01	.0208639	2013m2
15	29705.9	2013-03-01	.0194408	2013m3
16	31398.5	2013-04-01	.055415	2013m4
17	31624.8	2013-05-01	.0071818	2013m5
18	32995.8	2013-06-01	.0424379	2013m6

To sum up, to do a VaR calculation, two parameters must always be given:

• The time frame during which a portfolio's performance is evaluated, also known as its holding or horizon period. In most cases, this will be a 1-day to 10-day window, but it might also be a monthly or weekly window.

• A certainty that we will not suffer a loss larger than our VaR. Standard values for the confidence interval are 95% and 99%, but any value between 0 and 1 can be assigned.

Figure 1 VaR at a 95% CL



(Source: Dowd, 2013)

VaR is a useful instrument for tracking market risk but has limitations. In the first place, VaR is commonly criticized for failing to provide any information regarding the worst possible loss, i.e., we have yet to determine what additional income we can lose above and beyond our VaR. An additional caveat when attempting to gauge past VaR is that the sample period selected must accurately reflect the future, an assumption that might only hold in some instances (Jorion, 2009). Dowd (2013) echoes the warning against placing too much faith in VaR, arguing that the metric is too simplistic to picture the dangers involved fully. Moreover, the VaR researcher will change from one model to another based on the framework assumptions chosen. Researchers are in a worse position if they rely on false information rather than none, as Taleb (1997) puts it. A pilot will lose control of the aircraft if one gives him a faulty altimeter. He will stare out the window if one does not give him anything to do. Market returns tend to cluster, with "big changes likely to be followed by huge changes, of either direction and tiny changes likely to be joined by little changes..." as the Polish scientist Benoit Mandelbrot observed as early as 1963 (Mandelbrot, 1963). Based on these observations, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model to account for variation in time series variance. Conditional variance, also known as conditional volatility, is defined as 2 t|t1, where t 1 indicates that the conditional is upon returns at time t 1. In addition, the square return r 2 t is a fair measure of the variance of the squared return, 2 t|t1. If we think of conditional volatility as a response variable and the lag squared returns as the covariates, we can write the ARCH model as a linear regression.

$$r_t = \sigma_{t|t-1}\varepsilon_t$$

$$\sigma^2_{t|t-1} = \omega + \alpha r^2_{t-1}$$

The resulting form of an ARCH (1) model would be.
When and are unknown parameters and t is a sequence of independent and identically distributed random variables having no mean or unit variance, and t is uncorrelated with rtj (j=1, 2,....).
According to Engle (1982), a generalized form of the aforementioned equation called the ARCH(q) model, is possible when q delays of the square returns are taken into account.

$$\sigma^2_{t|t-1} = \omega + \alpha_1 r^2_{t-1} + \alpha_2 r^2_{t-2} + \ldots + \alpha_q r^2_{t-q}.$$

The "ARCH order" refers to q in this context. The GARCH model was refined by Bollerslev (1986) & Taylor (1986) under the assumption that the conditional variance has p delays included.

$$\sigma^2_{t|t-1} = \omega + \beta_1\sigma^2_{t-1|t-2} + \ldots + \beta_p\sigma^2_{t-p|t-p-1} + \alpha_1 r^2_{t-1} + \alpha_2 r^2_{t-2} + \ldots + \alpha_q r^2_{t-q}$$

In this case, q is the ARCH, p is the GARCH order, ω, α, and β are positive parameters to be taken (Cryer & Chan, 2008). Based on the discussion and relevant literature, the appropriate methodology (Arch, Garch) is employed to calculate the stock returns and volatility.

Results

An information criterion is applied to determine how well a given model fits a given dataset. One can choose which model to employ depending on the data presented here. There are various information criteria, but some have gotten more focus than others. According to Mantalos and Javed (2013), the Akaike Information Criterion (AIC) should be used for the GARCH models with greater (p, q)-dimensions. In contrast, the Hannan-Quinn information criteria (HQC) should be used for low-dimensional models. One possible explanation for AIC is
AIC = −2 log(ι) + 2k
Where k is the total number of free model parameters and is the probability function's maximal value, the model with the lowest Akaike Information Criterion (AIC) value should be chosen when choosing between many equally plausible models. In the Equation, the first term quantifies how well the model fits the data, and the second term is the cost function that reduces the attractiveness of models with additional parameters to avoid overfitting. It has been shown that (Akaike, 1974).
HQC= −2 log(ι) + 2k log(log(T))
In which k is the number of model parameters, T is the total number of observations, and is the maximal value of a likelihood function. Similar to AIC, a low HQC score indicates a good model fit. According to research (Hannan & Quinn, 1979). Time-varying variance is represented by heteroscedasticity (volatility). The degree to which the data depend on the recent past is modeled as Conditional, as well as the feedback mechanism's autoregressive infusion of past data into the present. The GARCH model is a mechanism for incorporating historical variations into explaining future variances. GARCH explicitly endorses using a model to investigate the sequential reliance of volatility as a time-series technique. Comparatively to other time-series models, GARCH models accurately describe heteroscedastic time series. In 1986, Bollerslev created GARCH, an expansion of Engle's (1982) original ARCH volatility modeling method. He created GARCH to provide a model that relies on fewer assumptions and is simpler.

Also, Nelson (1991) created a logarithmic model to show and evaluate the conditional variability contained in the unobserved variable. He labeled this phenomenon exponential GARCH (EGARCH). Inspired by Nelson's EGARCH, the derivative model GJR-GARCH was created, which accounts for the asymmetric nature of a shock to a given variable. The GARCH model, which was first put into practice in the financial markets by Christoffersen et al. (2004), has since found widespread and extended use in various fields.

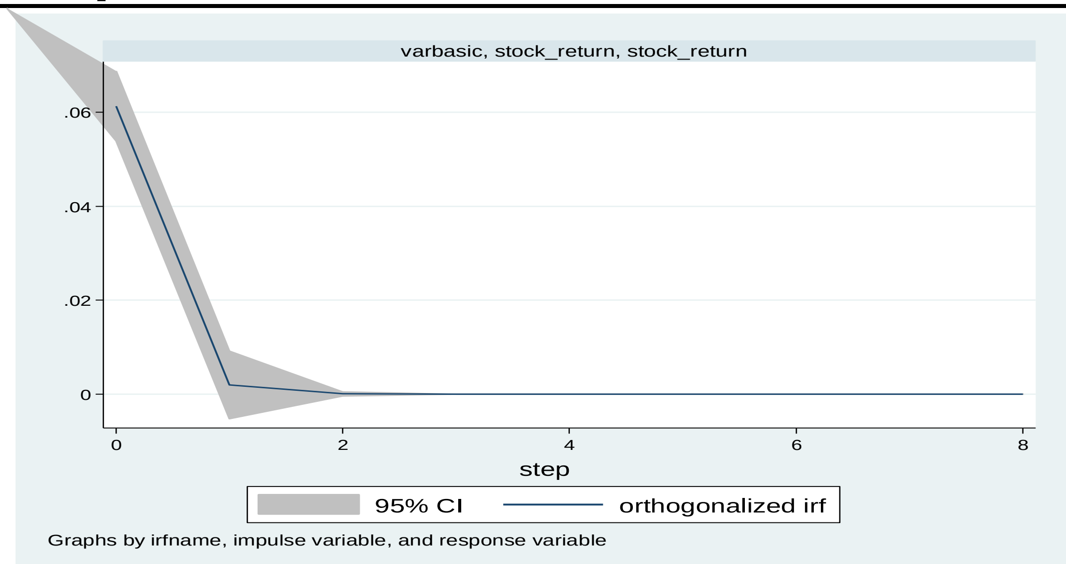
Descriptive statistics

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
closing	132	57679.165	17006.588	20108.16	87143.008
stock return	132	.003	.09	-.743	.209

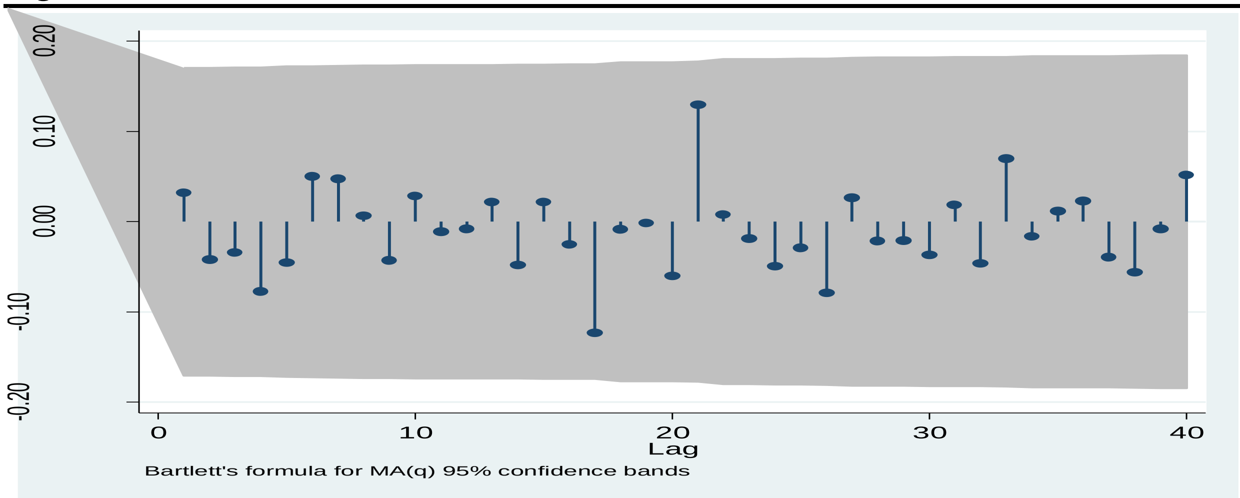
The table shows descriptive for the dataset of daily returns starting in January 2012 and ending on December 31st, 2022. The mean standard deviation and observation are shown as well.

Figure 1 Graph of Stock Returns



The graph above is made just for the understanding of stock returns that how they decreased or increased over time in the last ten years in the KMI-30 index. With the 95% confidence interval, .06 to 0 and some negative returns were also observed.

Figure 2 Auto Correlation of Stock Returns



In the autocorrelation, the stock returns show the above results. Some of the values are positive but some values are on the negative side in correlation. This also shows how volatile the market is in the last ten years.

Table 2 Garch results

The important values in the above table to be considered are the standard error, Z value, and p-value of the test. By default, the estimation output describes the estimation sample and the method used for calculating the coefficient standard errors in the initial variance terms as well. The results

Sample: 2012m1 - 2022m12	Number of obs	=	132
Distribution: Gaussian	Wald chi2(1)	=	3.69
Log-likelihood = 160.7208	Prob > chi2	=	0.0549

show that in the KMI-30 index the stocks are persistent across the years.

Table 2 Overall Results Garch 1,1

Stock_return	**Coef.**	OPG **Std. Err.**	**Z**	**P>z**	**[95% Conf.**	**Interval]**
months	-.0002814	0.0001466	-1.92	0.055	-.0005686	5.87E-06
_cons	.2000903	0.1033394	1.94	0.053	-.0024512	0.4026318
ARCH						
L1.	1.65273	0.110591	14.94	0.000	1.435975	1.869484
_cons	.0019979	0.0003016	6.63	0.000	.0014069	0.002589

The basic approach was to identify how AI can help us in the investing decisions of investors in the stocks of KMI-30. The STATA software made it easy to know the variance of the stock volatility and the future direction of stocks.

Discussion

Value-at-risk (VaR) serves as a vital risk metric, offering a quantifiable assessment of risks and providing a probability-based insight into potential future developments or the likelihood of risk events occurring. It is important to note that VaR is not confined to market price risk alone; it can be applied to various types of risk, making different risk positions comparable through a unified risk measure (Scherpereel, 2005). The resulting consolidated VaR is expressed in monetary terms (Fricke, 2006), making it easily comprehensible for management and decision-makers within an organization. Consequently, the risk associated with a portfolio comprising diverse financial instruments can be quantified and compared with other risk types within the same organization or similar risks in rival companies. VaR is a versatile risk metric applicable across sectors, as it can be applied to almost any quantifiable risk. This universality makes VaR a valuable risk metric for users (Bonke, 2007), and it is commonly used by companies across various industries, with financial institutions often incorporating it into their financial reports (Fricke, 2006). However, the focus should extend beyond the magnitude and historical data from the previous year to encompass the underlying assumptions and computation methods used. This additional information is crucial for meaningful comparisons with other companies. Our empirical investigations reveal that the choice of the computation model significantly influences VaR results. VaR has faced criticism regarding its conceptual underpinnings despite its interpretability and flexibility. Our empirical analysis demonstrates that VaR models effectively quantify market price risk and provide insights into future developments. However, these models may need more reliability in predicting risks, as they often exceed the projected maximum loss in each computation model. In a real-world scenario, such as a trader in a bank where the latest accepted VaR often determines trading limits, frequent breaches of the predicted maximum loss could have severe consequences, even threatening the bank's existence (Saita, 2007).

Consequently, the predictive accuracy of the VaR computation procedure must be continually evaluated through backtesting analyses, and the model's foundational parameters, such as the historical time horizon, may require adjustments. This study is done to determine how AI can save investor time and minimize risk. Moreover, these models are supported by literature that helps minimize the risk at certain decision-making points.

Conclusion

This study has uncovered some new insights concerning our preferred index. Much earlier research isolated Bitcoin and applied GARCH modeling, while others included other prominent cryptocurrencies or a broader range of financial market assets. Hence, the findings can aid business owners, financiers, and others in making informed judgments about investing in AI. Study findings revealed that the ARMA (1, 1) -SGARCH volatility model provided the most accurate estimates of VaR for the KMI-30 Index. In addition, when it comes to estimating and measuring volatility, EGARCH is the best model. For the asymmetric models, the positive and statistically significant values of EGARCH's gamma1, gamma2, and distribution coefficients show that volatility reacts differently with bad news than good news. As a result, when economic news is poor, and returns are low, market volatility spikes sharply. Note that the research only included the 30 largest corporations by market cap. Further research, however, could broaden the scope of the study to incorporate autoregressive stochastic volatility (ARSV). In addition, expanding the scope of empirical research to incorporate different asset classes such as bonds, shares, and equity in a portfolio with the various asymmetrical and symmetrical models is possible.

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