Jongadsayakul, W. (2026). Determinants of value at risk for SET50 index futures contract. *Journal of International Studies, 19*(1), 227-242. doi:10.14254/2071-8330.2026/19-1/12

Journal of International Studies

Centre of Sociological Research

Scientific Papers

Determinants of value at risk for SET50 index futures contract

Woradee Jongadsayakul
Department of Economics, Kasetsart University, Thailand
fecowdj@ku.ac.th
ORCID 0000-0002-9807-2138

Abstract. SET50 Index Futures contract is the first and most actively traded equity index futures contract on the Thailand Futures Exchange. However, futures trading is risky and requires that investors understand factors affecting risk. Therefore, this study uses monthly data from May 2014 to December 2024 for identifying the determinants of SET50 Index Futures contract's risk, quantified by Value at Risk (VaR). To calculate VaR of SET50 Index Futures, this study employs parametric method using EGARCH model for estimating volatility. Factors, including macroeconomic factors, futures trading activity, and underlying SET50 Index factors, are included as independent variables in a regression model. Using ordinary least squares approach, the results show that inflation rate and rate of change in exchange rate are the only macroeconomic factors affecting SET50 Index Futures contract's VaR. In addition, volume and open interest of SET50 Index Futures as well as liquidity and past volatility of its underlying asset affect VaR. Therefore, investors and related agencies should track inflation rate and exchange rate since they are crucial factors affecting risk for SET50 Index Futures. Understanding the determinants of risk for SET50 Index Futures contract allows for better risk assessment, informed trading strategies, and more successful participation in the futures market.

Received: June, 2025
1st Revision: January, 2026
Accepted: March, 2026

DOI: 10.14254/2071-8330.2026/19-1/12

Keywords: Value at Risk, index futures, Thailand, volatility, EGARCH model

JEL Classification: G11, G23, G32

1. INTRODUCTION

Thailand is widely recognized as an emerging economy. From 1960 to 1996, Thailand's economy experienced a 7.5% average growth rate. Following the 1997-98 Asian Financial Crisis, the Thailand growth rate came down to 5% a year in 1999–2006. Thailand experienced a period of slower growth, reaching an average of 3.6% between 2010 and 2019. Following the COVID-19 pandemic, the annual growth rate dropped to an average of 2% between 2021 and 2024. To boost Thailand's economic growth and development, an efficient and strong capital market is crucial. For the development of efficient capital markets, the establishment of Thailand Futures Exchange (TFEX) in 2004 positively contributed to the development of financial system and capital market in Thailand. Although some derivatives instruments have been regularly traded in the OTC market, SET50 Index Futures as the first product to be traded on TFEX was launched in 2006. While derivatives are primarily used for risk management, there is doubt that the misuse of derivatives, such as credit default swaps and asset-backed securities, were one of causes of the 2008 financial crisis (Zhang, 2024). Since the derivatives market cannot be complete with only hedgers, speculative trading activity generates considerable liquidity. Derivatives can provide investors with access to a wide range of asset classes at lower cost. However, one of the key features of futures trading is leverage, not only offering the potential for greater profits, but also coming with more significant risks.

Compared to other futures and options contracts, SET50 Index Futures contract is the first and most active derivatives contract in TFEX. As shown in Table 1, SET50 Index Futures had the highest trading volume between 2023 and 2024, contributing around 47% of the total trade volume of TFEX. Trading volume of SET50 Index Futures grew at about 7% per annum over the last five years.

Table 1

Yearly Volumes of Futures and Options Traded on TFEX from 2020 to 2024 Unit: Number of contracts

Types of Contracts	2020	2021	2022	2023	2024
SET50 Index Futures	57,465,829	47,620,961	54,748,061	62,142,760	54,998,945
Single Stock Futures	47,386,674	70,326,055	57,065,032	42,299,081	37,219,227
Precious Metal Futures	10,818,307	11,960,055	12,158,417	11,146,209	12,261,087
Deferred Precious Metal Futures	3,413	1,626	1,766	2,078	5,087
Currency Futures	2,803,128	3,449,751	10,189,955	11,431,640	11,261,777
Agricultural Futures	17,597	16,002	13,565	7,762	10,470
SET50 Index Options	1,698,625	1,742,858	2,139,216	2,461,711	2,283,811
Total Market Volume	120,193,573	135,117,308	136,316,012	129,491,241	118,040,404
Daily Average Volume	494,623.76	560,652.73	565,626.60	532,885.76	483,772.15

Source: Thailand Futures Exchange (2025)

Liquidity in SET50 Index Futures market often attracts investors to TFEX as it enables investors to easily enter and exit positions, which is a major factor in driving investment interest. However, compared to its underlying asset, Jongadsayakul (2021) shows that SET50 Index Futures investment carries higher risk than stock investments with a correlation to the performance of SET50 Index. Therefore, the analysis of SET50 Index Futures contract's risk, quantified by Value at Risk (VaR), and its determinant is significant for enhancing portfolio optimization and implementing effective hedging strategies. VaR provides a probabilistic estimate of potential losses over a specified time horizon, allowing investors to assess downside risk in a precise and interpretable way rather than relying on volatility alone. By understanding the key determinants of VaR such as macroeconomic factors, futures trading activity, and the underlying market liquidity and volatility, investors can identify which factors most strongly influence risk exposure in SET50 Index Futures. This knowledge allows investors to anticipate how changes in economic conditions, sudden volatility spikes, or liquidity constraints may amplify potential losses. As a result, they can make more informed portfolio allocation decisions, including adjusting position sizes, timing market entry and exit more carefully, and selecting appropriate hedge ratios. These actions help limit downside risk, preserve capital during adverse market conditions, and improve the overall effectiveness of risk management strategies.

While a large body of literature has examined the relationship between spot and futures prices and the impact of futures trading on spot market volatility, relatively little attention has been paid to identifying the economic and market-based determinants of VaR for futures contracts, particularly in emerging derivatives markets. Previous studies such as Muzaffar (2011) and Kwon (2021) show several variables related to the macroeconomy play a key role in explaining VaR. While Muzaffar (2011) considers VaR as a proxy of market risk in Pakistani commercial banks, Kwon (2021) investigates the factors of Bitcoin's tail risk, quantified by VaR. While the relationship between macroeconomic conditions and VaR in futures markets remains largely unexplored, this study addresses this gap by explicitly incorporating measures of economic activity, monetary policy, and price and external stability as determinants of VaR. Therefore, focusing on Thailand Futures Exchange, this paper investigates the impact of economic growth rate, private investment growth rate, interest rate, inflation rate, exchange rate, futures trading activity, as well as underlying market liquidity and volatility on VaR of SET50 Index Futures.

The rest of the paper is organized as follows. The next section presents a brief literature review on VaR. The third section explains data and methodology. The fourth section contains two sub-sections, including a brief overview of the SET50 Index Futures and its underlying asset as well as estimation results for VaR and its determinants. Finally, we conclude the paper in the fifth section.

2. LITERATURE REVIEW

Value at Risk (VaR) is used to estimate the maximum potential loss of an investment over a specific time period, with a given confidence level. There are a lot of different methods of estimating VaR, including non-parametric method, parametric method, and semi-parametric method. Each method comes with its own set of advantages and disadvantages as discussed in previous studies such as Abad et al. (2014), Maxwell & Vuuren (2014), and Linsmeier & Pearson (2000). As the most frequently used non-parametric method, historical simulation uses historical data without making strong assumptions about returns distribution. Its results not only depend highly on the historical data but also react insufficiently to sudden changes in market conditions. On the other hand, parametric method relies on specific assumptions about the return distribution but incorporates time-varying conditional volatility. To capture the volatility clustering properties in financial data, the volatility models proposed in literature include the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models, the Stochastic Volatility (SV) models, and the Realized Volatility (RV) models. Previous studies, such as Lehar et al. (2002) and Fleming & Kirby (2003), show not much difference in estimating VaR using GARCH and SV models. Giot & Laurent (2004) compare the performance of the GARCH family model using daily returns with the performance of the RV model using intraday returns. They show that both models deliver equally adequate VaR forecasts. Although some studies, such as Brownlees & Gallo (2010), show that the RV model outperforms the GARCH family, empirical findings by Şener et al. (2012) suggest that asymmetric models, such as CAViaR Asymmetric and EGARCH, produce the most accurate VaR forecasts. Therefore, it is inconclusive to declare a single "best" volatility model in VaR estimation. For the semi-parametric method, it combines elements of non-parametric approach with elements of parametric approach. For example, volatility-weight historical simulation updates return information using the recent changes in volatility. It is considered superior to historical simulation in estimating VaR (Hull & White, 1998). However, its result is sensitive to the historical data set and volatility shifts.

Because volatility is a key input to VaR models, the characterization of volatility is important when implementing and testing VaR models. According to Shayya et al. (2023), the GARCH family model is the most widely used in the estimation of VaR, with an increasing trend, especially after 2008. The popular GARCH family models used in the VaR estimation are symmetric GARCH, exponential GARCH (EGARCH), the fractionally integrated asymmetric power ARCH (FIAPARCH), the fractionally integrated GARCH (FIGARCH), the asymmetric power ARCH (APARCH), the hyperbolic GARCH (HYGARCH) and the absolute value GARCH in the mean (AVGARCHM). With a focus on derivatives market, several studies focus on applications of various GARCH VaR models and evaluate their forecasting performance on commodity futures markets. Giot & Laurent (2003) compute VaR for long and short trading positions in metal, energy and agricultural futures markets. Their results suggest that skewed Student APARCH provides the best results. Empirical evidence by Füss et al. (2010) also shows the GARCH VaR models as recommend methods for estimating VaR of commodity futures. However, Zhang and Zhou (2024) combine autoregressive integrated moving average (ARIMA), support vector regression (SVR), and the peak-over-threshold (POT) method from extreme value theory, and compare this hybrid model with ARIMA–EGARCH, ARIMA–SVR, and ARIMA–EGARCH–POT using daily crude oil WTI futures data. Their results show that the ARIMA–SVR–POT model yields more accurate forecasts of returns and volatility and performs particularly well in capturing extreme tail behavior, outperforming the benchmark models. Lyu et al. (2025) utilize high-frequency data of Brent Crude Oil futures to examine the VaR forecasting performance. Their findings indicate that the simple GARCH, EGARCH, GJR-GARCH models are significantly outperformed by realized measures such as the realized bipower variation (BPV).

Several studies examine VaR estimation in the context of equity index futures. For example, Tang & Shieh (2006) consider the FIGARCH and HYGARCH models. For S&P and Nasdaq 100 stock index futures, the HYGARCH model with skewed Student-t distribution performs better than others. However, the FIGARCH model with skewed Student-t distribution is adequate to fit Dow Jones Industrial stock index futures. Kasman (2009) also calculates VaR using the FIGARCH models with Normal, Student-t, and skewed Student-t distributions. The skewed Student-t FIGARCH model performs better than the normal distribution in describing the return series in the Turkish futures market. In addition, Carchano et al. (2010) present empirical support that the ARMA-GARCH model with tempered stable innovations performs better than the one with normal innovations in predicting 1-day-ahead VaR for the S&P 500, DAX30, and Nikkei 225 futures. Wu (2018) conducts the empirical analysis of GARCH and conditional autoregressive (CARR) volatility models in estimating VaR of CSI-300 spot and futures index. The CARR VaR does a better job in VaR forecasting. For SET50 Index Futures market, Jongadsayakul (2021) show that asymmetric GARCH models, TARCH and EGARCH models, provide more accurate and efficient forecasts of VaR than symmetric GARCH model.

Most studies emphasize VaR estimation and efficiency testing using various methods and datasets. However, to the best of our knowledge, there are few empirical studies on VaR determinants. Muzaffar (2011) investigates five factors, namely exchange rate, interest rate, idiosyncratic risk, market liquidity, and political risk affecting market risk as measured by VaR. Interest rate risk and political risk factors are found to be determinants of market risk in commercial banks listed in Pakistan stock market. Kwon (2021) examine 30 potential drivers of Bitcoin's 5% and 1% VaR. Variables related to macroeconomy play a key role in explaining only Bitcoin's 1% VaR. While consumer sentiment index, US economic policy uncertainty index, exchange rates for EURO to US dollar, and returns on the corporate bond index show a significant relationship with Bitcoin's 1% VaR, variables related to commodities and the Chinese stock market exert significant effects on the Bitcoin's 5% VaR. On the other hand, Demirdöğen (2024) considers volatility index, foreign exchange risk, and commodity risk as market risk determinants and utilizes Random Forest algorithm for weighting of these risks on the portfolio. The VaR analysis is conducted on the portfolio consisting of four stocks with the highest trading volume in the banking index of Borsa İstanbul. Beyond the determinants of VaR, an expanding body of literature examines the determinants of systemic risk using VaR-based measures such as delta conditional value at risk. Kurter (2024) examines the effects of macroeconomic conditions on market-based systemic risk measures for European banks. Using delta conditional value at risk, marginal expected shortfall, and a systemic risk measure that calculates the capital required in the event of another crisis, the analysis shows that systemic risk increases markedly during major stress events, including the global financial crisis and the Brexit referendum. The results further indicate that systemic risk exhibits a stable long-run relationship with key macroeconomic variables such as EU industrial production, inflation, Euribor, and US equity market volatility, while the short-run effects of these variables differ in magnitude and direction.

Beyond studies on VaR determinants, prior research highlights the role of macroeconomic factors in financial market risk and uncertainty. Hasan et al. (2025) investigate the relationship between macroeconomic conditions and financial market risk in Bangladeshi mutual funds. Downside risk is measured using semi-standard deviation and lower partial moments, while downside risk-adjusted performance is assessed through the Sortino ratio and the Information ratio. Using panel data for 27 mutual funds, the results show that deposit rates, broad money supply, and GDP growth are positively associated with semi-standard deviation but negatively related to lower partial moments, whereas exports and remittances exhibit opposite effects across risk measures. A'yunin et al. (2025) also conduct panel data analysis to examine macroeconomic influence on financial risk in consumer cyclical sub-sector firms listed on the Indonesia Stock Exchange. The study shows that traditional macroeconomic variables, such as inflation and interest rates, do not significantly affect financial risk. However, investment-related factors play an important role, as long-term investments financed through long-term debt significantly increase financial risk. Abaidoo & Agyapong (2025) analyze the effects of macroeconomic risk and volatility on financial market uncertainty, with particular attention to the moderating role of governance and institutional structures. The results indicate that macroeconomic risk and exchange rate volatility increase financial market uncertainty across economies in the sub-region, while institutional quality and government effectiveness weaken the impact of macroeconomic risk, inflation uncertainty, GDP growth, and exchange rate movements on financial market uncertainty.

Other studies focus on the effects of macroeconomic conditions on stock market volatility. Muhammad et al. (2021) determine the impact of macroeconomic variables on the stock return volatility of commercial banks in Pakistan. The results show that interest rates, exchange rates, and the balance of payments have a positive effect on stock return volatility of commercial banks in Pakistan, while inflation exerts a negative effect. Unemployment is found to have no significant impact on volatility. Using multivariate GARCH models, Jakšić et al. (2025) show that macroeconomic variables, including inflation, interest rates, exchange rates, and commodity prices, significantly influence volatility in both developed and emerging markets. Volatility in emerging markets is found to depend mainly on exchange rate movements and commodity prices, while volatility in developed markets is primarily driven by interest rates and inflation. Besides the major macroeconomic factors, factors affecting volatility of asset or portfolio directly impact the estimated VaR. A large proportion of previous studies on futures market volatility investigate the relationship between volatility and futures trading activity, namely trading volume and open interest. Trading volume represents speculative demand, while open interest is closely tied to hedging in the futures market. Several studies, such as Xin et al. (2005) and Floros & Salvador (2016), evidence a positive relationship between futures volatility and trading volume, as well as a negative relationship between futures volatility and open interest. According to the mixture of distribution hypothesis proposed by Clark (1973), volumes and volatility are influenced by the rate of information flow to the market. Trading volume serves as a proxy for information flow in the market and is positively correlated to price variability. On the other hand, a higher open interest generally indicates increased market depth, leading to higher liquidity and greater capacity to absorb price fluctuations. In addition to futures trading activity's effect on volatility, factors related to underlying asset significantly impact futures market volatility. Li (2011) examines the effect of cash market liquidity on the volatility of stock index futures. The findings show that cash market liquidity is negatively associated with futures price volatility. Market volatility also affects the risk associated with futures trading. A higher underlying volatility increases the risk of losses in futures contracts due to a higher probability that the price of the underlying asset will move significantly in either direction.

Adding to the existing literature, the aim of this study is to identify what determines SET50 Index Futures contract's risk, quantified by VaR. The following hypotheses are tested in this study:

H1. Economic activity factors, namely economic growth rate and private investment growth rate, are related to VaR of SET50 Index Futures.

H2. Monetary policy factor, namely interest rate, is related to VaR of SET50 Index Futures.

H3. Price and external stability factors, namely inflation rate and exchange rate, are related to VaR of SET50 Index Futures.

H4. Futures trading activity factors, namely trading volume and open interest, are related to VaR of SET50 Index Futures.

H5. Underlying market factors, namely liquidity and volatility, are related to VaR of SET50 Index Futures.

3. METHODOLOGY

3.1. Data

To examine the determinants of SET50 Index Futures contract's risk, quantified by VaR, monthly data used in this paper consists of macroeconomic data, trading volumes and prices in both spot and futures markets, and open interest for the period from May 2014 to December 2024. Macroeconomic data, including Coincident Economic Index (CEI), Private Investment Index (PII), Consumer Price Index (CPI), the policy interest rate, and the exchange rates of USD/THB, are obtained from Bank of Thailand, while the rest is collected from SETSMART. The sample period starts after the SET50 Index Futures adjustment on the contract multiplier from THB 1,000 per index point to THB 200 per index point. The nearby quarterly futures contract is chosen in this study since it is the most active contract in SET50 Index Futures market. It is a common practice to construct the data set for SET50 Index Futures prices by rolling over from one expiring month contract to the next when trading volume and open interest of the expiring quarterly month contract are lower than those of the next quarterly month contract. Spot and futures returns are calculated by finding the first difference in the natural logarithms of the monthly closing prices in SET50 Index spot and futures markets, respectively.

3.2. Models

This section consists of three subsections as follows:

1. VaR Estimation

To calculate VaR of SET50 Index Futures, this paper employs parametric method using EGARCH model for estimating volatility. Assuming a long position in one SET50 Index Futures contract, the following equation shows the VaR estimation using the parametric method at significance level of α:

$$VaR_t = \left| F_t * 200 * \frac{\mu - (\sigma_t * Z)}{100} \right| \tag{1}$$

where F_t represents the monthly closing price of SET50 Index Futures at time t, μ is a percentage of mean return, σ is the conditional standard deviation of the return, expressed as a percentage, and Z is the Z-score corresponding to the significance level α. The Z values for confidence levels of 90%, 95%, and 99% are 1.2816, 1.6449, and 2.3263, respectively.

2. Volatility estimation

The EGARCH model proposed by Nelson (1991) is often considered a good choice, often outperforming other volatility models. The EGARCH model makes sure the positive conditional variance, regardless of the restrictions on the parameters. It also incorporates a leverage effect (γ), which captures the asymmetry in the impact of positive and negative shocks on volatility. The EGARCH (1,1) model is shown as follows:

$$\ln\left(\sigma_t^2\right)=\alpha_0+\alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|+\gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}+\beta_1\ln\left(\sigma_{t-1}^2\right) \quad (2)$$

where σ^2 is the conditional variance, and $\frac{\varepsilon}{\sigma}$ is standardized residual. For Value at Risk (VaR) estimation, the conditional standard deviation (σ) of SET50 Index Futures return is the square root of the conditional variance.

In addition, this paper employs the EGARCH (1,1) model to model return volatility patterns for SET50 Index returns. The square root of the conditional variance is used as a proxy of underlying market volatility.

3. Regression Model

This study analyzes the factors influencing the risk of SET50 Index Futures contracts, measured by Value at Risk (VaR), using Ordinary Least Squares (OLS) regression. Statistical inference is based on conventional standard errors, with heteroskedasticity-robust (White) and Newey–West standard errors reported as robustness checks. We classify the explanatory variables into five groups: economic activity factors, monetary policy factor, price and external stability factors, futures trading activity factors, and underlying market factors. Table 2 provides variable descriptions.

Table 2

Variable Descriptions

Types	**Variable Name & Symbol**	**Measurement**
Risk	Risk of SET50 Index Futures contracts (RISK)	Natural logarithm of VaR at a specified significance level (α = 10%, 5%, and 1%)
Economic activity factors	Economic growth rate (EG)	Difference between the natural logarithms of CEI for the current month and the previous month, expressed as a percentage
	Private Investment growth rate (PG)	Difference between the natural logarithms of PII for the current month and the previous month, expressed as a percentage
Monetary policy factor	Interest rate (INT)	Policy interest rate in percent
Price and external stability factors	Inflation rate (INF)	Difference between the natural logarithms of CPI for the current month and the previous month, expressed as a percentage
	Exchange rate (EX)	Natural logarithm of exchange rate for US dollar to Thai baht at the end of the month
Futures trading activity factors	Trading volume (TV)	Natural logarithm of monthly trading amount of SET50 Index Futures contracts
	Open interest (OI)	Natural logarithm of total number of SET50 Index Futures contracts that are currently outstanding at the end of the month
Underlying market factors	Liquidity (LIQ)	Natural logarithm of monthly volume of SET50 index
	Volatility (VO)	The square root of the conditional variance of SET50 Index return, expressed as a percentage

Since it is important to conduct unit root test for time series analysis, this paper employs the Augmented Dickey-Fuller (ADF) test to determine if the time series are stationary or not. If the variable is not stationary in levels, the first difference is used to transform non-stationary time series into a stationary one.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. SET50 Index Futures Market and Its Underlying Asset

SET50 Index Futures is a futures contract with SET50 Index as the underlying asset. It was launched in 2006 as the first derivatives contract traded in the Thailand Futures Exchange (TFEX). Assuming the standard normal distribution assumption, this study estimates the return volatility of SET50 Index and SET50 Index Futures using the EGARCH (1,1) model. Stationarity of the return series is tested using Augmented Dickey-Fuller (ADF) test. The ADF test results indicate that the null hypothesis of a unit root is rejected at the 1% significance level. Utilizing monthly data from May 2014 to December 2024, Table 3 shows the estimation results of the EGARCH (1,1) model.

Table 3

Estimation Results of the EGARCH (1,1) model for SET50 Index and SET50 Index Futures Markets

Market	**SET50 Index**		**SET50 Index Futures**	
	Estimated value	P-value	Estimated value	P-value
Mean Equation				
Constant	0.0581	0.8174	0.1756	0.5407
MA(7)	0.1281*	0.0603	0.1092	0.1891
MA(8)	-0.2422***	0.0026	-0.2318***	0.0004
Varaince Equation				
Constant (α_0)	1.0572***	0.0003	1.1569***	0.0095
ARCH (α_1)	-0.0955	0.4768	-0.1204	0.5347
Asymmetric (γ)	-0.4447***	0.0001	-0.4769***	0.0010
GARCH (β_1)	0.6089***	0.0000	0.5887***	0.0002
Residual Tests				
Q(12)	9.8138	0.457	10.146	0.428
ARCH-LM (1)	1.8913	0.1691	1.422	0.2331

Source: Authors' results. * indicates significance level at 0.10 level, ** indicates significance level at 0.05 level, *** indicates significance level at 0.01 level.

To test the validity of the estimated the EGARCH (1,1) model, this study employs a Ljung–Box Q statistic to assess the presence of serial correlation and a Lagrange Multiplier (LM) statistic to indicate the presence of ARCH effects. The p-values from the Ljung–Box Q test and the Lagrange Multiplier (LM) test are greater than the 5% significance level. This means there is no statistically significant evidence of serial correlation or autoregressive conditional heteroscedasticity in the model residuals. The residual test results confirm the appropriateness of the EGARCH (1,1) model for analysing volatility of the SET50 Index and SET50 Index Futures returns.

As indicated in Table 3, the mean equation incorporates lagged residuals at lags 7 and 8 for both SET50 Index and SET50 Index Futures cases. The coefficient of lagged residual at lag 7 is significant at the 10% significance level for SET50 Index only. On the other hand, the coefficient of lagged residual at lag 8 is significant at the 1% significance level for both SET50 Index and SET50 Index Futures. For the variance equation, the coefficient for the previous shock (α_1) is not statistically different than zero for both cases. However, the coefficient of lagged conditional variance (β_1) is considered statistically significant at the 1%

level for both cases. In addition, the asymmetric coefficient (γ) is negative and statistically significant at the 1% level for both cases, suggesting the presence of leverage effect in SET50 Index and SET50 Index Futures markets.

When comparing between SET50 Index and SET50 Index Futures markets as shown in Table 4, a 3.8285% monthly volatility in SET50 Index Futures market, as measured by the square root of the conditional variance, indicates higher volatility of the SET50 Index Futures than its underlying asset. While SET50 Index Futures market generates a positive average monthly return equal to 0.0978%, its underlying market witnesses negative return equal to -0.0446%. SET50 Index Futures tends to provide higher returns, but it also carries higher risks. The VaR represents the maximum possible loss that a portfolio is expected to experience over a specified period, at a specified significance level. With a portfolio containing only a long position in one SET50 Index Futures contract, the average monthly VaR estimates for SET50 Index Futures using the parametric method at significance levels of 10%, 5%, and 1% are 9,084.77 baht, 11,756.79 baht, and 16,768.40 baht, respectively. The average monthly trading volume of SET50 Index Futures is 3,595,973 contracts, with an open interest of 387,650 contracts at the end of month, while the SET50 Index has a monthly volume of 28,565,979,685 shares.

Table 4

Average Monthly Data by Markets (May 2014 – December 2024)

Average	SET50 Index	SET50 Index Futures
Returns	-0.0446%	0.0978%
Volatility	3.6910%	3.8285%
Volume	28,565,979,685 shares	3,595,973 contracts
Open Interest		387,650 contracts
VaR (α = 10%)		9,084.77 baht
VaR (α = 5%)		11,756.79 baht
VaR (α = 1%)		16,768.40 baht

Source: Authors' results.

4.2. Determinants of SET50 Index Futures Contract's Risk

This paper employs Ordinary least Square (OLS) to model the determinants of SET50 Index Futures contract's risk, quantified by VaR. The VaR estimation using the parametric method at significance level of 0.10, 0.05 and 0.01 is transformed using the natural logarithm. The OLS estimation provides the most efficient and unbiased estimates of the regression coefficients when its assumptions are satisfied. Table 5 presents descriptive statistics and the Augmented Dickey–Fuller (ADF) test results used to evaluate stationarity.

Table 5 presents the descriptive statistics, including the mean, median, maximum, minimum, and standard deviation, of all variables used in the analysis. The natural logarithm of VaR at the 10%, 5%, and 1% significance levels exhibits noticeable variation over the sample period, reflecting changes in downside risk under different confidence levels. The means and medians of the VaR measures are relatively close, suggesting limited skewness, while the increasing dispersion at lower significance levels indicates higher tail risk. The private investment growth rate has a higher mean (0.2237%) and a higher standard deviation (9.3065%) than the economic growth rate (mean = 0.1552% and standard deviation = 1.5327%), indicating stronger average growth and greater volatility. This suggests that private investment is more sensitive to changes in economic conditions than overall economic activity. The policy interest rate has a mean of 1.4473% and exhibits comparatively low volatility, as reflected by a small standard deviation (0.6185%), consistent with gradual adjustments in monetary policy. Although the monthly inflation rate is low on average (0.0752%), its relatively large standard deviation (0.4728%) indicates noticeable variability over time, reflecting intermittent periods of price instability. The exchange rate variable shows moderate variation, reflecting movements in the USD/THB rate over the sample period. For SET50 Index Futures market trading activity, the natural logarithm of trading volume has a mean of 15.0145 and a standard deviation of 0.4173, while the natural logarithm of open interest has a mean of 12.8035 and a standard deviation of 0.3535. Both variables have lower means and higher variability than the natural logarithm of underlying market volume, which has a mean of 24.0305 and a standard deviation of 0.2935. This indicates more pronounced fluctuations in market participation and investor positioning in the futures market, suggesting lower market stability and less consistent investor participation compared to the underlying equity market. Underlying market volatility, measured by the square root of the conditional variance of SET50 Index returns, exhibits pronounced fluctuations, consistent with periods of heightened market uncertainty. The one-month lag of the square root of the conditional variance of SET50 Index returns has a mean of 3.6973% and a standard deviation of 1.0529%, with values ranging from a minimum of 1.5594% to a maximum of 8.3977%. This range indicates substantial variation in market volatility over the sample period, reflecting shifts between relatively stable conditions and periods of heightened market uncertainty.

Table 5

Descriptive Statistics and ADF Test Results

Variable	Ln VaR (α = 10%)	Ln VaR (α = 5%)	Ln VaR (α = 1%)	EG	PG	INT	INF	EX	TV	OI	LIQ	VO(-1)
Mean	9.0745	9.3331	9.6889	0.1552%	0.2237%	1.4473%	0.0752%	3.5088	15.0145	12.8035	24.0305	3.6973%
Median	9.0925	9.3498	9.7044	0.1636%	-0.1303%	1.5000%	0.0330%	3.5041	15.0905	12.7570	24.0371	3.5615%
Maximum	9.8772	10.1302	10.4804	4.7370%	17.4780%	2.5000%	1.5902%	3.6355	16.0115	13.5306	25.1231	8.3977%
Minimum	8.2755	8.5425	8.9068	-7.1115%	-23.6820%	0.5000%	-2.0319%	3.4007	14.0069	12.0879	23.3701	1.5594%
Std. dev.	9.0745	9.3331	9.6889	1.5327%	9.3065%	0.6185%	0.4728%	0.0561	0.4173	0.3535	0.2935	1.0529%
ADF test in level	-6.1566	-6.1609	-6.1653	-7.5180	-2.7950	-2.1854	-8.8645	-2.4491	-3.8181	-3.3597	-6.3940	-5.4244
P-value	0.0000	0.0000	0.0000	0.0000	0.0621	0.2127	0.0000	0.1306	0.0187	0.0617	0.0000	0.0000
ADF test in 1st dif.						-3.7520		-7.9368				
P-value						0.0044		0.0000				

Source: Authors' results.

The ADF test results indicate that all variables, except interest rate and exchange rate, are stationary at level. Interest rate (INT) and exchange rate (EX) are non-stationary at their level but become stationary after taking the first difference. Therefore, the first difference of both interest rate (DINT) and exchange rate (DEX) are used to estimate the regression model as follows:

$$RISK_t = a_0 + a_1EG_t + a_2PG_t + a_3DINT_t + a_4INF_t + a_5DEX_t + b_1TV_t + b_2OI_t + c_1LIQ_t + c_2VO_{t-1} + e_t \quad (3)$$

where RISK as dependent variable is proxied by natural logarithm of VaR at significance levels of 10%, 5%, and 1%, and one month lag of underlying market volatility, VO(-1), as one of independent variables is proxied by the square root of the conditional variance in the EGARCH (1,1) model.

Table 6 presents pair-wise correlation between independent variables. The absolute values of correlation coefficient are less than 0.6 so there is no sign of multicollinearity.

Table 6

Correlation Matrix

	EG	PG	DINT	INF	DEX	TV	OI	LIQ	VO(-1)
EG	1.0000	0.2372	0.1420	0.3854	-0.1549	-0.0522	0.0114	-0.0374	-0.1316
PG	0.2372	1.0000	-0.0041	0.0265	0.0702	0.1748	0.0716	0.1433	-0.0702
DINT	0.1420	-0.0041	1.0000	0.0010	-0.0723	0.1673	0.2700	-0.0521	-0.0381
INF	0.3854	0.0265	0.0010	1.0000	-0.0070	0.0009	0.1043	0.1108	-0.0831
DEX	-0.1549	0.0702	-0.0723	-0.0070	1.0000	0.0590	-0.0290	-0.0665	-0.1376
TV	-0.0522	0.1748	0.1673	0.0009	0.0590	1.0000	0.5977	0.4844	0.1814
OI	0.0114	0.0716	0.2700	0.1043	-0.0290	0.5977	1.0000	0.1181	0.0963
LIQ	-0.0374	0.1433	-0.0521	0.1108	-0.0665	0.4844	0.1181	1.0000	0.2334
VO(-1)	-0.1316	-0.0702	-0.0381	-0.0831	-0.1376	0.1814	0.0963	0.2334	1.0000

Source: Authors' results.

In addition, tests for serial correlation and heteroscedasticity are conducted. As shown in Panel B of Table 7, the p-values from the Ljung–Box Q test at lag 12 and the Breusch-Godfrey Serial Correlation LM test at lag 12 are greater than the 5% significance level. Therefore, we cannot reject the null hypothesis of no autocorrelation at any order less than or equal to 12 at the 5 percent level of significance. The White test's p-values from three models are around 0.4 which is greater than 0.05, suggesting no statistically significant evidence of heteroscedasticity in the OLS regression. While this supports the use of conventional OLS standard errors (SE) in the results reported in Panel A of Table 7, Table 8 presents robustness checks using heteroskedasticity-robust (White SE) and Newey–West standard errors (Newey–West SE).

From Panel A of Table 7, the value of R-squared in regression analysis is around 39 percent, meaning that around 39 percent of the variation in the natural logarithm of monthly VaR at significance levels of 10%, 5%, and 1% is explained by the following variables: EG (economic growth rate), PG (private investment growth rate), DINT (change in policy interest rate), INF (inflation rate), DEX (rate of change in exchange rate), TV (SET50 Index Futures trading volume), OI (open interest in SET50 Index Futures market), LIQ (spot market liquidity), and VO(-1) (past spot market volatility). The F-statistic's p-value is 0 in all cases, meaning that we can reject the null hypothesis that all of the regression coefficients are equal to zero at the 0.01 level.

In testing the hypotheses, the estimated coefficients on EG, PG, and DINT are not statistically significant across the 90%, 95%, and 99% VaR specifications. Accordingly, the data do not provide empirical support for Hypotheses H1 and H2. These results contrast with the findings of Hasan et al. (2025), who report that GDP growth and deposit rates are positively associated with downside risk in Bangladeshi mutual funds. The study by Muzaffar (2011) also identifies interest rate risk as a key determinant of market risk in commercial banks listed on the Pakistan Stock Market. However, the finding of no significant impact of interest rate on VaR in the SET50 Index Futures market is consistent with the results of A'yunin et al. (2025) for consumer cyclical sub-sector firms listed on the Indonesia Stock Exchange. When considering price and external stability factors, the results show that the coefficients of INF and DEX are significant at the 0.10 level. Therefore, Hypothesis H3 cannot be rejected. An increase in the inflation rate leads to a significant decrease in VaR, while a percentage change in the exchange rate has a significantly positive impact on VaR. An increase in the inflation rate can increase demand and reduce risk for SET50 Index Futures investment since investors seek to hedge against the eroding purchasing power of money and potential price increases. On the other hand, for foreign investors holding Thai assets, a stronger USD can erode their returns when converted back to their home currency. This currency risk could lead to decreased demand and increased potential loss for an investment in SET50 Index Futures. The significant response of VaR to exchange rate is consistent with the evidence from Kwon (2021), while the negative effect of inflation rate on VaR is inconsistent with the findings of A'yunin et al. (2025).

Table 7

OLS Regression Results

Model	(A) 90% VAR		(B) 95% VAR		(C) 99% VAR	
Panel A: OLS Estimates						
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	14.7482***	1.9980	14.9701***	1.9796	15.2891***	1.9610
EG	-0.0119	0.0159	-0.0119	0.0157	-0.0118	0.0156
PG	-0.0008	0.0024	-0.0008	0.0024	-0.0008	0.0023
DINT	-0.0513	0.2414	-0.0507	0.2392	-0.0501	0.2370
INF	-0.0969*	0.0495	-0.0961*	0.0490	-0.0953*	0.0486
DEX	0.0241*	0.0129	0.0238*	0.0128	0.0234*	0.0127
TV	0.2113***	0.0763	0.2098***	0.0756	0.2083***	0.0749
OI	-0.1372*	0.0789	-0.1371*	0.0782	-0.1370*	0.0775
LIQ	-0.3160***	0.0885	-0.3133***	0.0877	-0.3106***	0.0869
VO(-1)	0.1387***	0.0210	0.1371***	0.0208	0.1354***	0.0206
R^2	0.3935		0.3930		0.3925	
Panel B: Diagnostic Tests						
Test	Statistic	P-value	Statistic	P-value	Statistic	P-value
F Test	8.4351	0.0000	8.4172	0.0000	8.3983	0.0000
Q (12)	11.241	0.508	11.393	0.496	11.554	0.482
LM Test	14.5799	0.2652	14.7199	0.2571	14.8662	0.2488
White Test	9.3347	0.4070	9.3526	0.4054	9.3705	0.4038

Source: Authors' results. Conventional OLS standard errors are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8

Robustness Checks Using Alternative Standard Errors

Model	(A) 90% VAR			(B) 95% VAR			(C) 99% VAR		
Variable	Coefficient	White SE	Newey–West SE	Coefficient	White SE	Newey–West SE	Coefficient	White SE	Newey–West SE
Constant	14.7482	2.1363	2.2621	14.9701	2.1173	2.2421	15.2891	2.0981	2.2219
EG	-0.0119	0.0161	0.0132	-0.0119	0.0159	0.0131	-0.0118	0.0158	0.0130
PG	-0.0008	0.0025	0.0028	-0.0008	0.0025	0.0027	-0.0008	0.0024	0.0027
DINT	-0.0513	0.2868	0.2996	-0.0507	0.2840	0.2967	-0.0501	0.2811	0.2937
INF	-0.0969	0.0556	0.0459	-0.0961	0.0551	0.0454	-0.0953	0.0545	0.0449
DEX	0.0241	0.0117	0.0108	0.0238	0.0116	0.0106	0.0234	0.0115	0.0105
TV	0.2113	0.0644	0.0630	0.2098	0.0639	0.0625	0.2083	0.0633	0.0620
OI	-0.1372	0.0806	0.0869	-0.1371	0.0799	0.0861	-0.1370	0.0791	0.0853
LIQ	-0.3160	0.0925	0.0989	-0.3133	0.0917	0.0981	-0.3106	0.0909	0.0972
VO(-1)	0.1387	0.0289	0.0310	0.1371	0.0286	0.0307	0.1354	0.0283	0.0304

The results for futures trading activity factors indicate statistically significant effects, consistent with Hypothesis H4. Several studies, such as Xin et al. (2005) and Floros and Salvador (2016), provide evidence of a positive relationship between futures volatility and trading volume, as well as a negative relationship between futures volatility and open interest. These results confirm that futures trading activity factors affecting asset or portfolio volatility directly influence the estimated VaR. The coefficient of TV is positive and significant at 1% level, suggesting a positive relationship between SET50 Index futures trading volume and VaR. Higher trading volume often indicates increased market activity and participation, which can increase price fluctuations and thus upsurge risk. On the other hand, the coefficient of OI is negative and significant at the 10% level, implying a negative relationship between open interest and VaR in SET50 Index Futures market as suggested by Smit and Louw (1996). The coefficient of OI remains significant under conventional and White standard errors but becomes statistically insignificant when Newey–West standard errors are applied. The evidence should therefore be interpreted with caution. One possible explanation for this negative association is that a high open interest naturally suggests greater market depth and liquidity, which can reduce risk by providing more opportunities for traders to enter and exit positions without significantly affecting prices. Given the sensitivity of the result to the use of Newey–West standard errors, this interpretation should be viewed as suggestive rather than conclusive. For factors related to underlying market, this paper considers liquidity and past volatility. The results show the significant coefficients of both factors at the 0.01 level, providing empirical support for Hypothesis H5. A more liquid spot market leads to a significant decrease in VaR, while a more volatile spot market in the past increases VaR value. A liquid and less volatile SET50 Index market lowers risk and makes SET50 Index Futures contract more attractive to investors.

Overall, the main results are robust to alternative standard error corrections. In particular, statistical inference for the reported coefficients is largely unchanged when using White and Newey–West standard errors, and in some cases statistical significance strengthens under these corrections. The only notable exception is open interest, whose statistical significance weakens under Newey–West standard errors.

5. CONCLUSION

SET50 Index Futures contract is the first and most actively traded equity index futures contract on the Thailand Futures Exchange (TFEX). This makes it appealing to a wide range of investors, from those seeking to capitalize on market trends to those aiming to manage risk in their portfolios. However, futures trading is risky and requires that investors understand factors affecting futures contract's risk. Using ordinary least squares regression, this study employs monthly data from the period from May 2014 to December 2024 for identifying factors influencing the risk of SET50 Index Futures contracts, measured by Value at Risk (VaR). To calculate VaR of SET50 Index Futures, this study employs parametric method using EGARCH(1,1) model for estimating volatility. Independent variables in a regression model can be divided into five following groups: 1) economic activity factors, including economic growth rate and private investment growth rate 2) monetary policy factor, including change in policy interest rate 3) price and external stability factors, including inflation rate and rate of change in exchange rate 4) futures trading activity factors, , including trading volume and open interest 5) underlying market factors, including liquidity and past volatility.

The estimation results show that inflation rate and rate of change in exchange rate are the only macroeconomic factors affecting SET50 Index Futures contract's VaR. Either a decrease in the inflation rate or an increase in the rate of change in exchange rate leads to an increase in the maximum potential loss from an investment in SET50 Index Futures. For factors related to SET50 Index Futures market trading activity, the results show positive coefficient of trading volume and negative coefficient of open interest. For factors related to underlying SET50 Index, when underlying market is either less liquid or more volatile in the past, the risk of SET50 Index Futures contract gets higher too. Overall, the main findings are broadly robust to alternative standard error specifications. Therefore, investors and related agencies should understand and track inflation rate and exchange rate since they are important macroeconomic factors affecting VaR of SET50 Index Futures. In addition, both futures trading activity and underlying SET50 Index factors are crucial for understanding market dynamics and making informed investment decisions.

Investors can use the results of this study to adjust their investment plan and minimize the risk associated with their investment in SET50 Index Futures.

This study is subject to some limitations. The analysis relies on monthly data with a relatively small sample size of 127 observations, which limits the scope for sub-sample analyses and the assessment of structural changes over time. Extending the observation period to include earlier crises, such as the 2008 global financial downturn, and comparing the effects of the 2008 crisis with those of the COVID-19 pandemic would allow an assessment of whether macroeconomic and market-specific factors exert similar impacts on VaR across different crisis periods. In addition, the current study employs a linear OLS framework, which may not fully capture nonlinear relationships in futures markets, and uses the policy interest rate as the only monetary factor. Future research could explore alternative econometric methods to better account for nonlinear dynamics and extend the analysis by incorporating external factors, such as foreign direct investment and political risk, as well as additional monetary indicators, including money supply growth.

ACKNOWLEDGEMENT

The author is thankful to Department of Economics, Faculty of Economics, Kasetsart University for financial support to carry out this research.

REFERENCES

Abad, P., Benito, S., & López, C. (2014). A comprehensive review of Value at Risk methodologies. *The Spanish Review of Financial Economics, 12*(1), 15-32. https://doi.org/10.1016/j.srfe.2013.06.001

Abaidoo R, Agyapong E.K. (2025). Financial market uncertainty and the macro economy: the role of governance and institutional quality. *EconomiA*, *26*(1), 89–107. https://doi.org/10.1108/ECON-02-2023-0034

A'yunin, I., Rinofah, R., & Maulida, A. (2025). Analysis of the influence of macroeconomic factors on financial risk. *Indonesian Interdisciplinary Journal of Sharia Economics*, *8*(2), 4028-4052. https://doi.org/10.31538/iijse.v8i2.6286

Brownlees, C.T., & Gallo, G.M. (2010). Comparison of volatility measures: a risk management perspective. *Journal of Financial Econometrics, 8*(1), 29-56. https://doi.org/10.1093/jjfinec/nbp009

Carchano, O., Rachev, S.T., Kim, Y.S., Sun, E.W., & Fabozzi, F.J. (2010). Forecasting VaR in spot and futures equity markets. Retrieved June 13, 2025, from https://methods.stat.kit.edu/download/Forecasting_VaR_in_Spot_and_Futures_Equity_Markets.pdf

Clark, P.K. (1973). Subordinated stochastic process model with finite variance for speculative processes. *Econometrica 41*(1), 133–153. https://doi.org/10.2307/1913889

Demirdöğen, Y. (2024). Market risk analysis with value at risk models using machine learning in BIST-30 banking index. *Adam Academy Journal of Social Sciences, 14*(1), 63-89. https://doi.org/10.31679/adamakademi.1387201

Fleming, J., & Kirby, C. (2003). A closer look at the relation between GARCH and stochastic autoregressive volatility. *Journal of Financial Econometrics, 1*(3)*,* 365-419. https://doi.org/10.2139/ssrn.430400

Floros, C., & Salvador, E. (2016). Volatility, trading volume and open interest in futures markets. *International Journal of Managerial Finance, 12*(5), 629-653. https://doi.org/10.1108/IJMF-04-2015-0071

Füss, R., Adams, Z., & Kaiser, D.G. (2010). The predictive power of value-at-risk models in commodity futures markets. *Journal of Asset Management, 11*(4), 261-285. https://doi.org/10.1057/jam.2009.21

Giot, P., & Laurent, S. (2003), Market risk in commodity markets: a VaR approach. *Energy Economics, 25*(5), 435-457. https://doi.org/10.1016/S0140-9883(03)00052-5

Giot, P., & Laurent, S. (2004). Modelling daily Value-at-Risk using realized volatility and ARCH type models. *Journal of Empirical Finance, 11*(3), 379-398. https://doi.org/10.1016/j.jempfin.2003.04.003

Hasan, S.M., Tawfiq, T.T., Hasan, M.M., & Islam, K.M.A. (2024). Risk in the shadows: Macroeconomic shifts and their effects on Bangladeshi mutual funds. *Investment Management and Financial Innovations*, *21*(4), 371–384. https://doi.org/10.21511/imfi.21(4).2024.30

Hull, J., & White, A. (1998). Incorporating volatility updating into the historical simulation for value at risk. *Journal of Risk, 1*(1)*,* 5-19. https://doi.org/10.21314/JOR.1998.001

Jakšić, P., Pjanić, M., Milošević, M., Marjanović, D., Dudić, B., & Stošić, L. (2025). Impact of macroeconomic factors on stock indices volatility: a GARCH Analysis for USA, Germany, Serbia and Croatia. *Computational Economics*. https://doi.org/10.1007/s10614-025-11170-1

Jongadsayakul, W. (2021). Value at risk estimation of the SET50 index: Comparison between stock exchange of Thailand and Thailand futures exchange. *Journal of International Studies, 14*(1), 227-240. https://doi.org/10.14254/2071-8330.2021/14-1/16

Kasman, A. (2009). Estimating value-at-risk for the Turkish stock index futures in the presence of long memory volatility. *Central Bank Review, 9*(1), 1-14.

Kurter, Z.O. (2024). How macroeconomic conditions affect systemic risk in the short and long-run?. *The North American Journal of Economics and Finance*, *70*, 102083. https://doi.org/10.1016/j.najef.2024.102083

Kwon, J.H. (2021). On the factors of bitcoin's value at risk. *Financial Innovation, 7*(1), 1-31. https://doi.org/10.1186/s40854-021-00297-3

Lehar, A., Scheicher, M., & Schittenkopf, C. (2002). GARCH vs. stochastic volatility: Option pricing and risk management. *Journal of Banking & Finance, 26*(2–3), 323-345. https://doi.org/10.1016/S0378-4266(01)00225-4

Li, J. (2011). Cash trading and index futures price volatility. *Journal of Futures Markets, 31*(5), 465-486. https://doi.org/10.1002/fut.20478

Linsmeier, T.J., & Pearson, N.D. (2000). Value at risk. *Financial Analysts Journal, 56*(2), 47-67. https://doi.org/10.2469/faj.v56.n2.2343

Lyu, Y., Yi, H., Qin, F., Liu, J., Ke, R., & Gao, D. (2025). Forecasting the value at risk of the crude oil futures market: Do high-frequency data help?. *Journal of Management Science and Engineering, 10*(3), 279-296. https://doi.org/10.1016/j.jmse.2025.01.001

Maxwell, D. & Vuuren, G. (2014). A review and update of value at risk. *Journal for Studies in Economics and Econometrics. 38*(3). 79-102. https://doi.org/10.1080/10800379.2014.12097273.

Muhammad, N., Ahmad, W., & Khan, Y. (2021). Impact of macroeconomic factors on stock returns volatility of commercial banks in Pakistan. *Global Economics Review*, *6*(3), 31-40. https://doi.org/10.31703/ger.2021(VI-III).04

Muzaffar, Z. (2011). Determinants of VAR in commercial banks of Pakistan. Retrieved October 31, 2024, from https://ssrn.com/abstract=1916210

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347-370. https://doi.org/10.2307/2938260

Şener, E., Baronyan, S., & Mengütürk, L.A. (2012). Ranking the predictive performances of value-at-risk estimation methods. *International Journal of Forecasting, 28*(4), 849-873. https://doi.org/10.1016/j.ijforecast.2011.10.002

Shayya, R., Forradellas, M. T.S., & Terceño, A. (2023). Value-at-risk models: a systematic review of the literature. *Journal of Risk, 25*(4), 1-23. https://doi.org/10.21314/JOR.2022.053

Smit, E.V.D.M., & Louw, M.W. (1996). The relationship between volatility, volume and open interest: Some evidence from the South African futures market. *South African Journal of Business Management, 27*(4), 113-121. https://doi.org/10.4102/sajbm.v27i4.816

Tang, T.L., & Shieh, S.J. (2006). Long memory in stock index futures markets: A value-at-risk approach. *Physica A: Statistical Mechanics and its Applications*, *366*(1), 437-448. https://doi.org/10.1016/j.physa.2005.10.017

Thailand Futures Exchanges. (2025). Annual report 2024. Retrieved June 13, 2025, from https://media.tfex.co.th/tfex/Documents/2025/Apr/TFEXAnnualReport2567.pdf

Wu, C. (2018). Measuring and comparing the value-at-risk using GARCH and CARR models for CSI 300 index. *Theoretical Economics Letters, 8*(6), 1179-1187. https://doi.org/10.4236/tel.2018.86078

Xin, Y., Chen, G., & Firth, M. (2005). The determinants of price volatility in China's commodity futures markets. *China Accounting and Finance Review, 7*(1), 124-145.

Zhang, C., & Zhou, X. (2024). Forecasting value-at-risk of crude oil futures using a hybrid ARIMA-SVR-POT model. *Heliyon, 10*(1), e23358. https://doi.org/10.1016/j.heliyon.2023.e23358

Zhang, J. (2024). Assessing the impact of derivatives on the 2008 financial crisis and the effectiveness of subsequent regulatory reforms. *Advances in Economics, Management and Political Sciences, 98*(1), 125-130. https://doi.org/10.54254/2754-1169/98/2024OX0140