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Estimating the precision of market risk within the tiger cub economies' region through VaR backtesting

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ABSTRACT

The purpose of this paper is to estimate the stock market risk exposure within the Tiger Cub Economies regions in calm and stormy stock market conditions. The secondary objective of the empirical research is to determine the reliability and accuracy of the stock market risk model used by most banking sectors within the region as the primary tool for mitigating potential systemic risk. The precision of the stock market risk model was assessed using the 250-day trading data of major indices from five emerging ASEAN countries or known as the Tiger Cub Economies stretching from January 2019 until December 2020. It consists of two sub-samples which are known as pre-COVID-19 pandemic and during COVID-19 pandemic. The current study contributes to the existing literature on the ability of VaR-HS model in estimating accurate stock market risk exposure in light of the recent pandemic COVID-19 within the Tiger Cub Economies region. Interestingly, it is also evident that inaccurate VaR-HS tend to overestimate the risk and VaR-GARCH tends to severely underestimate the measures during extreme market conditions. Finally, by recalibrating models that severely over/understate the risk during pandemic stormy market conditions in SETi and VNI indices, it is also imperative that RiskMetrics EWMA could improve the estimation measures in an extreme market event by putting more weights on the most recent volatility memory. The current study reveals new insights where in the event of a crisis, HS-VaR estimates tend to be overstated while GARCH-VaR measures could be understated where it is evident that EWMA-VaR estimates could provide a better measure of stock market risk exposure, particularly during stormy periods.

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1. Introduction

The financial crisis of 2007-2008 has left an indelible mark on the world. Bubbles produced in the market eventually burst forth in an epic moment of a huge recession. This devastated the entire economy and harmed millions of individuals, including many who were not investing in mortgage-backed investments, like a few others in history. Many economists attributed most of the blame to liberal mortgage lending policies, which allowed many consumers to take up far more debt than they could afford. According to the Federal Reserve of Cleveland, more than 500 banks failed between 2008 and 2015, compared to a total of 25 in the preceding seven years. Furthermore, it is now more concerning since the COVID-19 pandemic elevated banks' systematic risk, albeit to a lesser level than the global financial crisis (Pham, Powell, and Bannigidadmath, 2021).

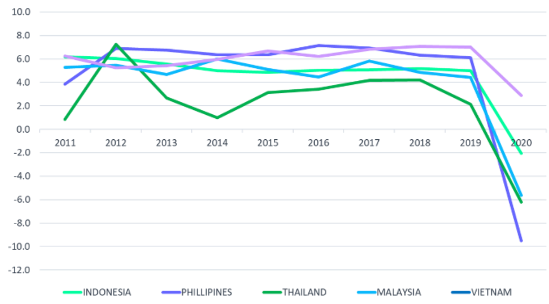

Figure 1: The Tiger Cub's GDP Growth Per Capita (annual %)

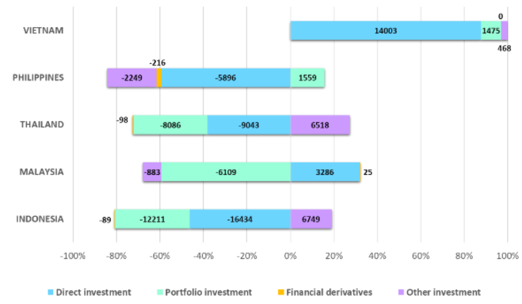

Figure 2: The Tiger Cub's Investment Composition (average values from 2017 to 2021)

Source: Key Indicators Database, Asian Development Bank/Economic Research and Regional Cooperation Department (ERCD)

The recent and unprecedented coronavirus disease outbreak (COVID-19) in 2019 has caused panic in the global financial market. According to the World Bank (2020), COVID-19 might precipitate a major recession, resulting in a drop of one-third of GDP and almost 70% of total employment in emerging and developing nations. Efforts to contain the pandemic's spread through economic shutdown had worsened the pattern of declining potential growth and productivity growth over a multi-decade period, particularly in emerging and developing countries with limited low-income healthcare capacity. Since the beginning of 2020, the COVID-19 pandemic ravaged countries that were once hailed as Asian Tiger Cub Economies† (Kuusinen et al., 2019). In recent years, each of these countries' GDP trended downwards dramatically. Thailand's GDP, which was growing at more than 6% a year at the start of the decade, only rose by 1.98% in 2019 before dramatically declining to -6.33% in 2020 due to the pandemic. Meanwhile, Malaysia's growth slowed from 4.6% to 3.06% during the same period before further sloping down to -6.86% in 2020. In Indonesia, GDP slowed from 6.2% in 2010 to 5% in 2019 and had a significant deceleration.

One obvious trigger of this deceleration was the decline in investment rates especially because there were fewer diversification efforts made to the investment portfolio composition amongst these countries.

† Indonesia, Malaysia, Philippines, Thailand and Vietnam have been nicknamed the 'tiger cub economies', an allusion to the 'Asian tigers' – Hong Kong, South Korea, Taiwan, and Singapore, who all achieved high levels of economic development in the latter half of the 20th century through export-led growth with high technology content. (Kuusinen et al., 2019)

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For example, figure 2 shows the average values composition of International Investments in the recent five years (2017-2021) derived from the financial account of each country which comprises portfolio investments, direct investments, financial derivatives, and other investments (Asian Development Bank, 2022). There was a clear gap in the diversification of the countries' investments, particularly the portfolio investment that experienced negative growth in Thailand (-8,086 million $USD), Malaysia (-6,109 million $USD) and Indonesia (-12,211 million $USD) respectively. This followed a medium-term trend in Malaysia, Indonesia, and Thailand, which was precipitated by the 1997-1998 East Asian Crisis, when investment rates fell by at least a quarter from prior highs of close to 40% of GDP to about 30%. Malaysian investment decreased even further in the 2010s, reaching barely 19% of the GDP by 2019. Indonesia 's investment also dropped sharply, from 40% of its GDP in 2010 to 30% in 2019. During the epidemic year of 2020, investment in all these countries fell again.

The properties of VaR are very essential to provide banks with good information to manage their assets and prepare sufficient capital allocations to cushion them against any unfavorable uncertainty in the market, especially in extreme market conditions. Due to the significance of VaR, the Basel Committee amended the Basel Accord in 1996, which required all banks to use daily VaR calculations when assessing their capital adequacy versus market risk exposure. To one extent, in 1997, the Securities and Exchange Commission of the United States instructed all the banks to provide a report of VaR as the main measurement of the market risk exposure. This showed how important VaR is in financial risk management. However, little is to be confirmed about the relevancy of VaR, especially before financial catastrophic events (hereafter, calm period) and during financial catastrophic events (henceforth, stormy period) such as before and during the COVID-19 pandemic. Despite challenges from rising pandemic breakouts, the Asia-Pacific region is estimated to remain the world's fastest-growing region, with a 6.2 percent growth rate in 2021 (IMF World Economic Outlook, 2021). However, the gap between Asian advanced economies such as China and the emerging market in the region is widening due to the gap in vaccination coverage and policy support which were expected to remain below pre-pandemic levels.

With the resurgence of unpredictable pandemic dynamics, vaccination efficacy against viral variants, supply chain disruptions, and potential global financial spillovers from US financial liberalization in the context of local financial vulnerabilities, the risks were skewed to the downside. The COVID-19 pandemic had negatively affected the stock market of countries around the world, including the emerging ASEAN countries. Although few past studies emphasized that VaR was best used to measure market risk during calm periods (Mak and Meng, 2014), yet in the case of the COVID-19 pandemic, there is still no solid evidence that the finding can be practical. Hence, this study tried to conduct a precision analysis of VaR in the context of pre- and during Pandemic COVID-19 in the emerging ASEAN countries. This study took into consideration the basic test, the so-called POF Test, which stands for the proportion of failure, and measures whether the number of exceptions is in accordance with the level of confidence. The current study also considered the Basel regulatory framework's current practice in assessing the level of market risk exposure, which is the traffic light approach at a 99% confidence level.

2. Literature review

Many academics and practitioners were eager to come up with the best model for measuring market risk, in line with the increased attention to various risk management strategies (Jian and Li, 2021; Salisu, Demirer, and Gupta, 2022). Since the pioneering work done by Markowitz (1952), who developed the portfolio theory in diversifying investment risk, theory-related finance, particularly in risk management, saw significant advancement. In this study, risk was measured by the standard deviation dispersion in mean and average returns. According to this theory, the asset's class is of high consideration in selecting the best investment position incorporating wealth distributions. A few years ahead, Sharpe (1964) proposed the Capital Asset Pricing Model (CAPM) as an evaluation and measurement tool for handling a portfolio's market risk by using covariance as related to the market factors such as beta and market index.

While believing that the return measurement in previous models and theories does not provide an indication of the real value of the risk, Morgan, and Reuters (1996) insisted on coming out with a better model that can portray the real value of the market risk called VaR. To date, investigations on VaR estimates have filled a significant portion of the current literature on risk management. The studies of VaR have rapidly grown continuously over the years after its formal introduction in 1994 by RiskMetrics. The initial idea of VaR was for the purpose of measuring market risk, which was to assess the upper limit loss incurred by a financial operator over a specified time horizon and for an assumed confidence level under normal market situations (Jauri and Taivonen, 2002; Jorion, 2009; Tsay, 2010; Braione and Scholtes, 2016; Merlo, Petrella and Raponi, 2021). Essentially, the modeling of VaR estimates provides an answer to one question: how much may an investment lose over a particular time horizon under specified probability for a given value in percentage or ringgit? (Morgan and Reuters, 1996). Simply put, VaR can be transcribed into the worst-case scenario that a portfolio could lose in an extreme event with a slight chance of occurrence within a particular period.

Development of VaR methodologies has been very intensive and continuously expanding. Up to now, there are three main approaches that are widely used in estimating VaR namely historical, analytical, and stochastic simulation approaches. However, in considering the normality assumption of a return series, there are three main approaches to be used which are the parametric approach, non-parametric approach, and semi-parametric approach. The parametric approach assumes that the return distribution is explicit rather than normally distributed. As a result, the confidence level is known analytically in this approach. RiskMetric (EWMA), GARCH and variance-covariance approaches are among the examples of parametric models in estimating VaR. Engle (1982) created the Autoregressive Conditional Heteroscedasticity (ARCH) model, which was the first study to demonstrate heteroskedasticity in asset volatility. Since then, considerable research has been done with the extension of model complexity such as the GARCH family models under both univariate and multivariate settings, stochastic models of volatility including the simpler Exponentially Weighted Moving Average (EWMA) model (Brooks, 2014). According to Brooks, the EWMA model was among the most widely used type of model on the univariate GARCH family models. In fact, there was an important finding to ponder in the study of Karlsson, Zakkrisson & Nilsson (2016) when comparing the performances of GARCH, EGARCH, GJR and EWMA models in both calm and stormy periods of the financial crisis. The best model for estimating VaR was determined to be EWMA with Gaussian specification, especially during the stormy period of the financial crisis. This could be due to the benefits of EWMA having a simple structure with only one memory as compared to other GARCH-type models which usually consisted of two kinds of memory where the coefficient estimation from the past period could be different from the present day. This could cause biasness in the volatility estimation. In addition, Pattarathammas, Mokkhavesa & Nilla-Or (2008) also came out with evidence that EWMA model with Gaussian distribution which appeared to be the best model in estimating the market risk as compared to GARCH with Gaussian distribution, HS-GARCH, HS-EWMA and EVT-GARCH model. The data was compiled using 10 MSCI World indices from 1993 to 2007. They also emphasized that the GARCH type model could be superior in the estimation if the sample size of the period is longer.

Despite the bad news on the non-performing GARCH type model as compared to EWMA based on the studies, GARCH still held a significant relevance in volatility forecasting today since its adoption by Bollerslev (1986), Nelson (1991) & Glosten et al. (1993). For instance, Hansen & Lunde (2001) advocated that there was no single conditional volatility forecasting model from a total of 330 types of models that could surpass the performance of GARCH (1,1) in producing better results in the prediction of DM/$ exchange rate and IBM stock prices data. Moreover, Bolgun (2004) compared the popular RiskMetrics system with the GARCH model in the Turkish capital market for the period of 2003 to 2004 and found that the GARCH model was the most suitable model for volatility jump estimations, particularly in emerging markets. Meanwhile, in a more recent study done by Degiannakis et al. (2014) comparing a special specification of the Fractionally Integrated GARCH (FIGARCH) model and a simple GARCH model prove that GARCH still outperforms its counterpart in estimating market risk in developed markets. In a more recent study, Muneer Shaik and Lakshmi Padmakumari (2022) emphasized the superiority of EWMA model in estimating VaR compared to the normal GARCH and HS model, especially within extreme market conditions such as during the Global Financial Crisis 2007 and the recent pandemic which started to wildfire in early 2020.

Meanwhile, in the nonparametric approach, there was no specific distribution assumed. The computation of VaR came from the standard theory of an order statistic, where the VaR was described from the multiple runs represented by numerous possible market price outcomes. Examples of non-parametric approaches were Historical Simulation and Monte Carlo simulations. The most recent innovation was the creation of semi-parametric techniques by merging some attributes of previous approaches. For example, by inducing the parametric GARCH method into the non-parametric Historical Simulation (HS) which created a Filtered Historical Simulation (FHS) technique.

According to Urbani (2004), the most important feature of VaR is its ability in segregating various sources of market risk into a single quantitative measure of the potential change in a portfolio value. This single quantitative figure can be used to explain the potential movement in the value and the market risk exposure of the firm. Davis and Fouda (1999) claimed that VaR had the ability to oversee the frequency of loss occurrence in return series. In addition, VaR can also assist the market user in evaluating their risk exposure, identifying the optimal asset allocations, determining the capital requirements, and devising the best strategies for portfolio selection. The fact that VaR can convey the market risk exposure in monetary value eases the market users to make decisions on their portfolio's optimization, classification, and selection in the market. Even though VaR has been a popular measure of market risk in recent years, there are still questions about how far VaR may be used to estimate market risk. To what extent will VaR be able to represent the stock market's volatile and unpredictable behavior?

For the purpose of this study, the subject matter focused on the aggregate market of the five emerging ASEAN countries or known as the Tiger Cub Economies (Kuusinen et al., 2019), which were proxied by their respective major indices . These major indices included the FTSE Kuala Lumpur Composite Index (KLCI) (Malaysia), IDX Composite (Indonesia), Thailand Stock Exchange Index (SETi) (Thailand), Philippines Stock Exchange Index (PSEi) (Philippines), and Viet Nam Index (VNI) (Vietnam).

3. Methodology

The precision of the stock market risk model was evaluated using data of 250 daily trading days of major indices[‡] from five emerging ASEAN countries or known as the Tiger Cub Economies[§] (Kuusinen et al., 2019) stretching from January 2019 until December 2020. It consisted of two sub-samples which are known as before and during the pandemic COVID-19 displayed in the following table 1. It was agreed by many researchers that different models are suitable to be used depending on different time periods (Ahmad Baharul Ulum, 2013). Therefore, the time frame of 250-daily trading data in 2020 was chosen since the bulk of the markets peaked mostly during January 2020, plunged during March 2020, and then rebounded after December 2020. Additionally, this time frame was chosen to represent the various impact of the COVID-19 effects on sampling stock markets from the beginning to the end of 2020. A 250-daily trading day prior to the pandemic is chosen to represent the calm period. All data was obtained from investing.com.

[‡] FTSE Kuala Lumpur Composite Index (KLCI) (Malaysia); IDX Composite (Indonesia); Thailand Stock Exchange Index (SETi) (Thailand); Philippines Stock Exchange Index (PSEi) (Philippines); Viet Nam Index (VNI) (Vietnam).

[§] The term Tiger Cub economies refers collectively to the strongest five economies of Southeast Asia. This includes the economies of Indonesia, Malaysia, the Philippines, Thailand, and Vietnam (Kuusinen et al., 2019)

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Table 1: Sub-sample period

Market	Period of study	Justification
Before the Pandemic (Calm Period)	January 2019 – December 2019	A 250-daily trading day prior to the pandemic was chosen to represent the calm period.
During the Pandemic (Stormy period)	January 2020 – December 2020	Most southeast Asian countries started to hit the bear cycle since WHO announced there was a cluster of unknown pneumonia cases in Wuhan City, Hubei Province, China. The stock market peaked after WHO declared COVID-19 a pandemic that reached a global spread of 118,000 cases in over 110 countries on the 3rd January 2020. (Johns Hopkins, 2022)

The market risk model was estimated using Value-at-Risk (VaR) that was formulated in equation 1.

$$VaR^{t} = \mu_t \alpha \sqrt{D_t} \tag{1}$$

The indices of the markets at time $_t$ are denoted as $\mu_{t,}$ σ reflects the standard deviation of the security returns and the holding period of (h) is depicted as $D_{t.}$ All the VaR estimates were tested using non-parametric Historical simulation (HS) and a parametric test via Generalized autoregressive conditional heteroskedasticity (GARCH1,1) that was developed by Bollerslev (1986).

Under the model of GARCH with normal distribution, the assumption of ε_t should be conditionally normally distributed with a conditional variance. One of the important assumptions made in the GARCH model is the variance pattern of returns which always followed the predictable process. The estimation procedure started with the analysis of descriptive statistics, and stationarity test using the Augmented Dickey fuller test (1981) and Phillips Perron (1988). The findings suggested that all the emerging countries data were sufficient at level. The next procedure was to calculate VaR diagnosed with both serial correlation and heteroskedasticity test and finally to backtest the estimation using the Kupiec's test, the most widely known test based on failure rates proposed by Kupiec (1995). Kupiec's test, also known as the POF-test (proportion of failures), measured whether the number of exceptions was consistent with the confidence level." ("Forecasting electricity price volatility with the Markov-switching ...") Under the null hypothesis of the model being 'correct', the number of exceptions followed the binomial distribution. Hence, the only information required to implement a POF-test was the number of observations (T), number of exceptions (χ) and the confidence level (c) (Dowd, 2006). The null hypothesis stated that the observed failure rate is equal to the failure rate, which is recommended by the confidence interval. Furthermore, the goal of accepting the null hypothesis was to prove that the model was accurate. In the case where the amount of likelihood ratio was greater than the critical value of the χ^2, the conclusion about rejecting the null hypothesis and model inaccuracy would be made. The likelihood ratio test, is expressed through the following:

$$LR_{POF} = -2\, ln[(1-p)(T-\chi)\, p^{x}] + 2ln[(1-\chi/T)^{(T-x)}(T-\chi)^{x}] \tag{2}$$

According to Jorion (2009), the exact definition of the likelihood ratio test is "a statistical test that calculates the ratio between the maximum probabilities of a result under two alternative hypotheses. The maximum probability of the observed result under the null hypothesis is defined in the numerator, and the maximum probability of the observed result under the alternative hypothesis is defined in the denominator. The decision is then based on the value of this ratio. The smaller the ratio is, the larger the LR-statistic will be. If the value becomes too large compared to the critical value of X^2 distribution, the null hypothesis is rejected. According to statistical decision theory, the likelihood-ratio test is the most powerful test in its class." In the case where the amount of likelihood ratio is greater than the critical value of the X^2, the conclusion about rejecting the null hypothesis and model inaccuracy would be made.

It is worth noting that, for the purpose of simplicity, the Basel Committee (1996b) specified a methodology for backtesting proprietary value-at-risk measures. Banks were to backtest their one-day 99% value-at-risk results (i.e., value-at-risk before scaling by the square root of 10) against daily profit and loss. It was left to national regulators whether backtesting was based on clean or dirty P&L's. Backtests were performed quarterly using the most recent 250 days of data. Based on the number of exceedances (exceptions), the value-at-risk measure would be categorized as falling into one of three colored zones:

Table 2: The Basel Committee traffic light backtests

Zone	Number of exceedances	Multiplier, k	Cumulative probability assuming q*=0.99
	0	3.00	0.0811
	1	3.00	0.2858
	2	3.00	0.5432
	3	3.00	0.7581
	4	3.00	0.8922
	5	3.40	0.9588
	6	3.50	0.9863
	7	3.65	0.9960
	8	3.75	0.9989
	9	3.85	0.9997
	More than 10	4.00	0.9999

The Basel Committee (1996b) defined green, yellow, and red zones for backtesting proprietary one-day 99% value-at-risk measures, assuming $\alpha + 1 = 250$ daily observations. For banks whose value-at-risk measures fell in the yellow zone, the Basel Committee recommended that, at national regulators' discretion, the multiplier k used to calculate market risk capital charges be increased above the base level 3, as indicated in the table. The committee required that the multiplier be increased to 4 if a value-at-risk measure fell in the red zone. Cumulative probabilities indicate the probability of achieving the indicated number of exceedances or less. They were calculated with a binomial distribution, assuming the null hypothesis $q^* = 0.99$. ("Backtesting Value-at-Risk with Coverage Tests") The data is analyzed using Microsoft Excel and EViews 12 software.

4. Findings

Table 3 depicts the descriptive statistics of the return distributions of the major indices of the tiger cub countries in both calm and stormy periods. The highest mean (0.000644) is recorded in the series of VNI during stormy periods, and the lowest mean (-0.000298) is observed in the same index series during its calm period. Additionally, all the indices are observed to have high kurtosis which is more than 3 which indicates that all the return series have fat tails (leptokurtic distribution). Furthermore, the rejection of the null hypothesis from the Jarque-Bera test confirms the non-normality traits in the return distributions of all indices. Finally, the return series are observed to be stationary at level based on the test of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The calculations of daily VaR under HS method do not require any distributional assumption since it depends heavily on the historical return series.

Table 3: Descriptive statistics and unit root tests of the return series

Indices	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF	PP
IDX Calm	8.48E-05	0.010032	-0.510854	3.986787	21.01703	-10.6467	-5.79752
					(*0.00027*)***	*(0.0001)****	*(0.0001)****
IDX Stormy	8.48E-05	0.010032	-0.510854	3.986787	21.01703	-13.8528	-26.9366
					(*0.00027*)***	*(0.0001)****	*(0.0001)****
KLCI Calm	-0.00025	0.006898	-0.797180	4.985491	67.54334	-7.0907	-14.8943
					(*0.00001*)***	*(0.0001)****	*(0.0001)****
KLCI Stormy	0.000121	0.012187	-0.031684	8.65200	332.8033	-14.1238	-23.11371
					(*0.00001*)***	*(0.0001)****	*(0.0001)****
PSEi Calm	-0.000242	0.011509	0.2627890	2.777177	3.394602	-22.79252	-22.89238
					(*0.183177*)	*(0.0001)****	*(0.0001)****
PSEi Stormy	-5.80E-05	0.020675	-1.527426	12.84491	1106.817	-9.277864	-23.29305
					(*0.00001*)***	*(0.0001)****	*(0.0001)****
SETi Calm	-0.000353	0,007600	-0.221995	3.788096	8.523146	-9.89539	-16.7985
					(*0.01410*)***	*(0.0001)****	*(0.0001)****
SETi Stormy	7.52E-05	0.018739	-1.344637	12.32941	981.9804	-22.8854	-5.9055
					(*0.00001*)***	*(0.0001)****	*(0.0001)****
VNI Calm	-0.000298	0.013979	-0.569806	4.319119	31.65409	-9.79990	-23.9652
					(*0.00001*)***	*(0.0001)****	*(0.0001)****
VNI Stormy	0.000644	0.014414	-1.193968	7.695172	289.0299	-18.6887	-8.78884
					(*0.00001*)***	*(0.0001)****	*(0.0001)****

*Notes: 1. JB test statistics are based on Jarque-Bera (1987) and are asymptotically chi-square distributed at 2 degrees of freedom. 2. Figure in the parentheses denote the p-value. ** and *** indicate significance at 5% and 1% level.*

Table 4 presents the results of daily VaR for 250 trading days during the calm and stormy periods. For the purpose of our study, three different confidence levels which are 95%, 99% and 97.5% were employed following several recommendations by the Basel committee as discussed in the previous section. It is interesting to know that the estimation of VaR increases when the confidence levels are set at a higher level. By observing risk estimates in the indices returns, it was observed that the highest VaR was realized mostly during the extreme market event of the pandemic, which is during the stormy period of the study (2020). Specifically, HS-VaR at 99% confidence level tend to generate the highest risk estimates in all countries namely -5.01% (IDX), -3.66% (KLCI), -7.50% (PSEi), -7.66% (SETi) and -5.25% (VNI).

Other than that, GARCH (1,1) had severely failed to provide justifiable risk estimates, particularly in the earlier expectation that GARCH could capture the clustering of market volatility. By looking at the VaR generated under GARCH specification, most series displayed the tendency of GARCH to understate the actual risk in the markets. It is known that computing VaR is critical for banks, enterprises, and institutional investors to make wise financial decisions to cushion any potential losses while at the same time mitigating other types of risk such as capital risk, liquidity risk and solvency risk. Therefore, it is very crucial that the VaR estimate is calculated with the least estimation error and in the most accurate manner. For this purpose, the backtesting process was conducted by using the unconditional test namely the Kupiec POF test and the Traffic Light approach following the current practice of regulatory framework. Under this approach, only the 99% confidence level was taken into account following the Basel Accord.

Table 4: VaR estimates for daily 250 trading days during calm and stormy market

	Calm Period		Stormy Period		Calm Period		Stormy Period	
	HS	GARCH	HS	GARCH	HS	GARCH	HS	GARCH
	IDX				SETi			
95%	-1.83%	-1.53%	-2.74%	-0.90%	-1.21%	-1.14%	-2.08%	-1.31%
97.5%	-2.03%	-1.84%	-4.14%	-1.12%	-1.69%	-1.38%	-3.96%	-1.58%
99%	-3.68%	-2.19%	-5.01%	-1.37%	-2.22%	-1.66%	-7.66%	-1.90%
	KLCI				VNI			
95%	-1.21%	-1.34%	-1.89%	-0.82%	-2.57%	-1.58%	-2.85%	-0.98%
97.5%	-1.58%	-1.61%	-2.58%	-1.00%	-3.34%	-1.88%	-3.59%	-1.20%
99%	-2.28%	-1.93%	-3.66%	-1.20%	-4.10%	-2.24%	-5.25%	-1.45%
	PSEi							
95%	-1.83%	-0.84%	-2.74%	-0.94%				
97.5%	-2.16%	-1.01%	-4.14%	-1.17%				
99%	-2.24%	-1.22%	-7.50%	-1.43%				

The backtesting of VaR estimates is very crucial, especially when it involves capital and liquidity management. Kupiec's POF-test was used in this case to examine whether the number of exceptions is too large in statistical terms. According to Nieppola (2009), the POF-test should give some meaningful results, even though the number of observations is limited to one year, especially with lower confidence levels. The test statistics for each portfolio and confidence level are calculated by plugging the data (number of observations, number of exceptions, and confidence level) into the test statistic function. As an example, consider the IDX index illustrated as follows, for which we observed 12 exceptions -or also known as the number of failures or exceedances- at 95% confidence level over 250 trading days during a calm period (January 2019 to December 2019).

The corresponding LR-statistic is calculated as follows:

$$LRPOF = -2\ln\left[(1-0.05)(250-23)\ 0.0523\right] + 2\ln\left[(1-23/250)(250-23)\ (23/250)23\right]$$
$$= -1.30$$

The POF test statistic as depicted above (-1.30) is much lower than the critical value of χ^2 for a 1-day trading interval at a 95% confidence level which is 3.842 χ^2 (Chi Square), indicating that the model is accurate in providing good market risk precision during calm market conditions. By calculating the statistics for the other indices and confidence levels in a similar fashion, we obtained results as shown in Table 5 below.

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Table 5. Backtesting - Kupiec POF likelihood test

	Calm period				Stormy period			
	X	LR_{POF}	χ^2	Model precision	X	LR_{POF}	χ^2	Model precision
	IDX Composite							
HS								
95%	23	-1.30	3.84	accepted	12	-4.44	3.84	accepted
97.50%	7	-2.48	5.02	accepted	6	-2.19	5.02	accepted
99%	2	-0.62	6.63	accepted	3	-0.99	6.63	accepted
GARCH								
95%	20	-3.57	3.84	accepted	53	57.26	3.84	rejected
97.50%	2	3.29	5.02	accepted	44	84.48	5.02	rejected
99%	5	0.13	6.63	accepted	30	85.53	6.63	rejected
	FTSE KLCI							
HS								
95%	13	0.02	3.84	accepted	12	-4.44	3.84	accepted
97.50%	6	0.01	5.02	accepted	7	-2.48	5.02	accepted
99%	1	1.18	6.63	accepted	3	-0.99	6.63	accepted
GARCH								
95%	18	-4.55	3.84	accepted	20	-3.57	3.84	accepted
97.50%	10	-1.74	5.02	accepted	10	-1.74	5.02	accepted
99%	5	0.13	6.63	accepted	5	0.13	6.63	accepted
	PSEi							
HS								
95%	13	-4.83	3.84	accepted	13	-4.83	3.84	accepted
97.50%	7	-2.48	5.02	accepted	7	-2.48	5.02	accepted
99%	3	-0.99	6.63	accepted	3	-0.99	6.63	accepted
GARCH								
95%	68	103.60	3.84	rejected	57	68.71	3.84	rejected
97.50%	53	120.49	5.02	rejected	40	69.80	5.02	rejected
99%	40	136.69	6.63	rejected	34	105.22	6.63	rejected
	SETi							
HS								
95%	18	-4.55	3.84	accepted	39	23.16	3.84	rejected
97.50%	9	-2.23	5.02	accepted	29	34.39	5.02	rejected
99%	5	0.13	6.63	accepted	15	23.77	6.63	rejected
GARCH								
95%	15	-5.13	3.84	accepted	35	15.38	3.84	rejected
97.50%	11	-1.05	5.02	accepted	28	31.59	5.02	rejected
99%	7	2.93	6.63	accepted	15	23.77	6.63	rejected

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	VNI							
HS								
95%	22	-2.16	3.84	accepted	30	7.11	3.84	rejected
97.50%	13	0.88	5.02	accepted	23	18.79	5.02	rejected
99%	5	0.13	6.63	accepted	17	30.63	6.63	rejected
GARCH								
95%	24	-0.35	3.84	accepted	32	10.22	3.84	rejected
97.50%	18	8.35	5.02	rejected	26	26.22	5.02	rejected
99%	13	17.47	6.63	rejected	23	54.01	6.63	rejected

Notes: X is realized number of exceptions, LRPOF is test statistics for Likelihood Ratio Proportion of failure, χ^2 is chi-squared distribution values at the 95%, 99% & 97.5% percentile with 1-degree of freedom. The model is accepted if LRPOF t-statistics exceed the value of X^2 for each percentile. Model is rejected if otherwise.

Since both risk models for SETi and VNI during stormy periods failed to pass the accuracy tests, the risk measures were recalibrated by using another counterpart model to GARCH in capturing the volatility of the market, namely the RiskMetrics EWMA model. In line with the findings recorded by Muneer Shaik and Lakshmi Padmakumari (2022), Karlsson et al., (2016), Brooks (2014) and Pattharathammas et al. (2008), it was evident that EWMA-VaR estimates could provide a better measure of market risk exposure, particularly during stormy periods. As can be seen in Table 6, both HS-VaR and GARCH-VaR failed to pass the backtesting which signaled the inaccuracy of market risk estimates during extreme events like the COVID-19 pandemic. To be more specific, most risk estimates, regardless of the confidence level, severely overestimated the risks under HS methods while the GARCH model seems to underestimate the market risk exposure. In a clearer illustration, we employed another time-varying volatility model which is EWMA of Riskmetrics which is putting a decaying factor or more weight on the recent volatility event compared to GARCH which tends to assume constant volatility over the period to test whether the risk modeling could improve. As expected, the model is recalibrated well and thus provides the necessary number of exceptions to be accepted as accurate. Considering this, it can be concluded that during the Stormy period, HS-VaR estimates tend to be overstated (for example -7.66% under 99% in SETi) while GARCH-VaR measures could be understated (for example -1.90% in SETi) where it is evident that EWMA-VaR exemplified that the accurate risk should be around -3.60%.

Table 6. Recalibration of VaR model using EWMA during Stormy period for SETi and VNI

	HS					GARCH					EWMA				
SETi	VaR					VaR					VaR				
95%	-2.08%	39	23.16	3.84	rejected	-2.08%	35	15.38	3.84	rejected	-2.54%	11	-3.88	3.84	accepted
97.5%	-3.96%	29	34.39	5.02	rejected	-3.96%	28	31.59	5.02	rejected	-3.03%	8	-2.48	5.02	accepted
99%	-7.66%	15	23.77	6.63	rejected	-7.66%	15	23.77	6.63	rejected	-3.60%	8	4.79	6.63	accepted
VNI	VaR					VaR					VaR				
95%	-2.85%	30	7.11	3.84	rejected	-2.08%	32	10.22	3.84	rejected	-2.01%	18	-4.55	3.84	accepted
97.5%	-3.59%	23	18.79	5.02	rejected	-3.96%	26	26.22	5.02	rejected	-2.40%	16	4.96	5.02	accepted
99%	-5.25%	17	30.63	6.63	rejected	-7.66%	23	54.01	6.63	rejected	-2.85%	13	17.47	6.63	rejected

To align the official backtesting framework with the computation of market risk capital requirement, the Basel Committee decided that the 99 % confidence should also be used in backtesting, although the

Committee recognized the fact that lower levels would be more suitable in model validation. On the other hand, the Committee insisted that using the 10-day holding period in backtesting was not a meaningful exercise, and therefore a period of one day should be used instead. (Basel Committee, 1996). Banks with substantial trading activity were required to set aside a certain amount of capital to cover potential portfolio losses. The size of this market risk capital was defined by the bank's VaR estimates. The current regulatory framework required that banks compute VaR for a 10-day horizon using a confidence level of 99% (Basel Committee, 2006). Under this framework, it was obvious that a strict backtesting mechanism was required to prevent banks from understating their risk estimates. Therefore, backtesting played a significant role in Basel Committee's decision to allow banks to use their internal VaR models for capital requirements' calculation (Jorion, 2001).

Like the POF-test, the Basel Committee 'traffic light' approach was an unconditional coverage test. It evaluated the frequency of exceptions (failure rate). This backtesting approach was used for regulatory purposes at the 99% confidence level, and exception ranges were provided for this confidence level by the regulatory framework. By taking out the range of exceptions occurring under a 99% confidence level, results of testing for the frequency of exceptions (unconditional coverage) using the Basel Committee 'Traffic Light' test are presented in Table 7. The findings show a weakness in the model accuracy during stormy periods compared to the models that were calibrated within the calm period. Interestingly, the GARCH model that was managed to capture the volatility clustering in a stormy market condition generates the highest number of exceptions compared to the Historical Simulation that is basically ignoring the stylized facts of the market return distributions such as the fat-tailedness and the clustering of the volatility.

Table 7. Basel Committee 'Traffic Light' (1996) approach

	Calm Period				Stormy Period			
	HS		GARCH		HS		GARCH	
Indices	X	Results	X	Results	X	Results	X	Results
IDX	2		5		3		30	
KLCI	1		5		3		5	
PSEi	3		40		3		34	
SETi	5		7		15		15	
VNI	5		13		17		23	

5. Conclusion

This study confirmed the relevancy of VaR before and during the financial catastrophic event of COVID-19. The market risk exposure was estimated within the Tiger Cub Economies regions in both calm and stormy market conditions and determined the reliability and accuracy of the market risk model of VaR, which was used by most banking sectors within the region as the primary tool for mitigating potential systematic risk. The fact that the COVID-19 pandemic increased banks' systematic risk underscores the significance of this study, as banks played a critical role in facilitating long-term economic growth and the BASEL required banks to use the most accurate market risk model to assess systematic risk. The use of VaR in calm periods may have been demonstrated previously, but the recalibration impact of RiskMetrics EWMA model adds to the proof that VaR is still relevant during stormy periods. Furthermore, we also found out that erroneous VaR calculated under HS tends to overestimate risk while VaR generated under the specification of GARCH tends to underestimate measures, especially under extreme market conditions. As a result, it is recommended that banks use VaR-EWMA to measure their systematic risk more accurately to avert catastrophic impact during market downturns. Nevertheless, because the data analyzed were limited to the countries within the Tiger Cub Economies regions, this finding may not be applied to the global market. Hence, the accuracy of VaR-EWMA in measuring systemic risk for different economies regions may be investigated in future research.

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Conflict of interest statement

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Ahmad Fauze carried out the research which includes the technical computations, wrote, and designed the research. Ninalyn Fridrict drafted the manuscript, added in few recent studies in the list of the literature review. Siti Julea assisted in preparing the manuscript formatting and critically contributed to the introduction part particularly the motive and the direction of the research. Maily Patrick helped in reviewing and revising the manuscript. Imbarine Bujang supervised the research progress and approved the article submission. All authors discussed the results and contributed to the final manuscript.