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Effects of Multiple Financial News Shocks on Tourism Demand Volatility Modelling and Forecasting

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Abstract: Even though both symmetric and asymmetric conceptions of news impacts are well-established in the disciplines of economics and financial markets, the effects of combining multiple news shocks on the volatility of tourism demand have not yet been delved into or gauged in any tourist destination. This work hypothesises and verifies that the news impact curve (NIC), conditional heteroscedastic volatility models, and multiple news shocks are suitable for forecasting the volatility of the Malaysian tourist industry. Among them, three primarily volatility models (GARCH, EGARCH, and GJRGARCH) are used in conjunction with five financial news shocks (FFNSs), namely the Kuala Lumpur Composite Index (KLCI), the United States Dollar Index (DXY), the stock performance of 500 large companies listed on stock exchanges (S&P500), Crude Oil (CO), and Gold Price (GP). Among the most significant findings of this study are the demonstration of monthly seasonality using conditional mean equations, asymmetry effects in EGARCH-FFNSs, and GJRGARCH-FFNSs models in conditional variance equations and 50 NICs, and the GARCH-FFNSs model's evaluation of the persistence influence of news shocks on monthly visitor arrivals in Malaysia. The GJRGARCH-FFNSs model is the best model for Malaysian tourism demand volatility forecasting accuracy. Furthermore, KLCI and Gold Price have the most substantial impact on the number of tourists to Malaysia. In addition, it should be emphasised that the methodological framework utilised in this study can be a useful tool for creating and forecasting the performance of symmetry and asymmetry impacts on tourism demand volatility.

Keywords: symmetric; asymmetric; news shocks; news impact curve; tourism demand volatility; forecasting; GARCH-FFNSs; EGARCH-FFNSs; GJRGARCH-FFNSs

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1. Introduction

Forecasting demand is vital for developing efficient business strategies in tourism management. Forecasting will assist tourism businesses in making decisions that are more likely to help them achieve their objectives (Smeral 2019). The economic environment, which influences tourism demand in numerous ways, must be considered when selecting a suitable forecasting method. Therefore, academics in this subject should deem it essential to comprehend and quantify the effects of unanticipated news shocks on the industry. Even though concepts and applications of news effects have been utilised extensively in the literature on global trading activities, economy, and financial management, there has been little effort to study or estimate how news shocks affect the volatility of tourism demand for any travel destination (Kim and Wong 2006).

This is because tourism demand's symmetric and asymmetric phenomenon exists under different news shocks. Generally, there is an asymmetrical relationship between

spending during times of struggle and periods of prosperity in terms of visitor demand (Smeral 2012). There are two possible manifestations of this: the first is a "symmetric constant," in which the same amount of financing is utilised during periods of prosperity and adversity. The second sign is a "symmetric mirror" because the amount saved during adversity is mostly equivalent to the amount spent during prosperity. Asymmetrical demand responses, meanwhile, have two distinct forms. In times of struggle, firms tend to save more money than in times of success or recovery, a tendency known as "asymmetric negative". Second, it is important to note that amid adversity, the amount of money saved is smaller than the amount of money spent, the phenomenon is known as an "asymmetric positive" (Bronner and de Hoog 2017).

Thus, news shocks are likely to have both explicit and implicit asymmetric and symmetric effects on the international or domestic tourist environment, depending on the conditions. As a form of retaliation for recent news, it is not unusual for the demand for travel to fluctuate. Few news shocks last for an extended period, while others fade away quickly and gradually (Balli et al. 2019; Coshall 2009; Smeral 2019). Furthermore, the level of shock visitors experience as a result of the news is likely to differ depending on the characteristics of the news; therefore, the effect of the news on tourism demand is likely to be immediate. In a society where new events occur on a constant basis, news bulletins covering these occurrences are spread worldwide through various types of mass media. It is possible that some news will have a desirable effect on tourists visiting specific areas, while other news will exert a negative impact (Chang and McAleer 2012; Falk 2015; Lim and Zhu 2017; Martins et al. 2017; Vita and Kyaw 2013; Yalcin et al. 2021).

Recent research has made substantial use of univariate volatility models in finance, but tourism is an exception where it has rarely been used (Coshall and Charlesworth 2011). According to the premise underlying volatility models, the tourism industry's demand is sensitive to economic shocks that cause substantial fluctuations, resulting in wildly fluctuating activity, such as symmetric and asymmetric occurrences. Economic changes are most likely the most significant negative shocks influencing tourism demand. Reducing taxes on tourism, investing in a location, or launching big marketing campaigns could all stimulate demand. For example, a drop in the value of a destination country's currency compared to the destination currency compared to home currencies is perceived favourably by visitors and potential travellers. This is expected to increase tourism demand in the country, whose currency has devalued. A reevaluation of a country's exchange rate, on the other hand, is regarded as negative news for that country (Balli et al. 2019; Coshall 2009).

Meanwhile, some studies concisely assess demand projections for international tourism (Gunter and Önder 2016; Jiang et al. 2020; Liu 2012; Qiu et al. 2021; Song et al. 2019; Wan and Song 2018). Amongst them, previous research has concentrated on forecasting global tourist demand utilising factors including currency fluctuations, gross domestic product (GDP) in the original country, consumer price index (CPI), income, and population size inability to forecast tourism demand in the international travel market (Hiemstra and Wong 2002; Santos and Cincera 2018; Schiff and Becken 2011; Stavárek 2007; Tang and Tan 2016; Turner and Witt 2001; Vatsa 2020), rather than the symmetric and asymmetric effects from these variables. Existing research studies of models forecasting international tourism demand, for instance, have indirectly accounted for the effect of volatile exchange rate fluctuations by converting the price factor within the tourist destination into the currency of the visitor country or by including a completely different factor in the international tourism demand function to account for the effect of volatile exchange rate fluctuations (Chang and McAleer 2012; Chi 2015; Croes and Sr 2005; Demir 2004; Falk 2015; Lim and Zhu 2017; Vita and Kyaw 2013; Yalcin et al. 2021). However, most previous research on the influence of the conflict on the tourist sector has focused on the surveillance of specific economic indices, such as the exchange rate, the consumer price index (CPI), the gross domestic product (GDP), and income, among other comparable indicators. Minimal efforts have been made to experimentally study how tourist demand is influenced by coupled economic indices, both in terms of their symmetric and asymmetric

impacts on tourism demand volatility. In addition, studies analysing the volatility of tourism demand using the concept of news shocks have been extremely limited, and this tendency is predicted to linger.

This paper aims to apply the various volatility models that can predict the monthly inbound tourism demand volatility in Malaysia and subsequently use these models to determine whether the tourist demand volatility is symmetric or asymmetric across five different financial news shocks. This study fills a gap in the existing literature and contributes to the body of knowledge by comparing the efficacy of various forecasting approaches in forecasting and predicting volatility. In addition, this is the first study to examine the monthly asymmetric and asymmetric effects of five financial news shocks on the volatility of Malaysian tourism demand and to compare the forecasting accuracy of volatility models in Malaysia based on data from nine of the most important international source markets. This study is notable because it contains five financial news shocks (KLCI, DXY, S&P500, crude oil, and gold price) that have never been examined or analysed together in the context of the tourism demand volatility forecasting research field (GARCH, EGARCH, GJRGARCH). Specifically, the results of this study will be utilised to determine, analyse, and comment on the most effective techniques for symmetric or asymmetric modelling and forecasting tourism demand volatility. In addition, this research study can be viewed as a crucial launching point for governments and enterprises to create and verify volatility forecasting models, which can better inform and provide accurate and dependable future tourism arrival projections to a wider variety of tourists.

The remainder of the contents of the study paper is organised as follows. In Section 2, a review of current research on the symmetric and asymmetric effects of news shocks in the tourism forecasting domain is provided, as well as an explanation of the major distinctions between the current work and previously published research. The third section elaborates on the models and methodologies. Sections 4 and 5 contain comprehensive descriptions of data resources, research processes, and research methods. Section 6 is devoted to a comprehensive assessment of the empirical findings. Based on the findings of this study, Section 7 details the findings and their consequences and provides recommendations for further research.

2. Literature Review

2.1. News Shocks in Tourism Demand Volatility

The news shocks exert direct or indirect effects on tourism demand. Figure 1 depicts the influence of news on tourism demand volatility (Chatziantoniou et al. 2013; Chen and Chiou-Wei 2009; Coshall 2009; Coshall and Charlesworth 2011; Dutta et al. 2021; Ertuna and Ertuna 2009; Hailemariam and Ivanovski 2021; Kim and Wong 2006; Muangasame and Dhevabanchachai 2003; Saglam and Ampountolas 2021; Tang et al. 2017; Wang 2009). As new events occur, newscasts report on them and promptly disseminate the information across the globe via multiple media outlets. Individual stories can have a beneficial impact on potential tourists, while some may exert a negative impact. It is conceivable that tourism demand may fluctuate in response to the latest news regarding the fluctuation of a target country's currencies or the occurrence of regional and global economic problems (Khalid et al. 2020; Schiff and Becken 2011; Tang and Tan 2016; Turner and Witt 2001; Vatsa 2020), political instability (Fletcher and Morakabati 2008), terrorism (Bhattarai et al. 2005), disease (Huan et al. 2004), natural disasters (Rosselló et al. 2020; Tsai and Chen 2011), oil prices (Becken and Lennox 2012), seasonality and other specific calendar-related holidays or events (Lim et al. 2008).

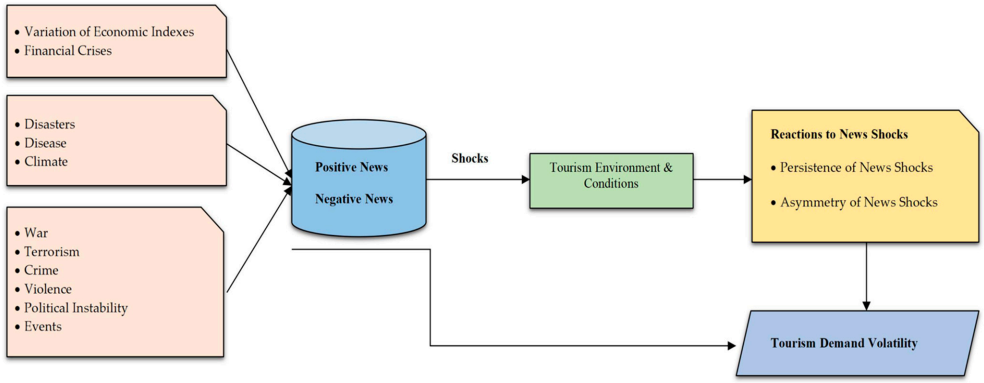


Figure 1. Effects of news shocks on tourism demand volatility (Source: from Kim and Wong (2006)).

2.2. Symmetric and Asymmetric Effects on Tourism Demand Volatility

Regarding the symmetric and asymmetric effects of tourist demand volatility, it is a well-established fact that travel-related offerings might be underpriced based on current market conditions (Quadri and Zheng 2010). Underestimating tourism demand generally results in overcrowding at admission points and tourist destinations, poor service quality, a tarnished image of the host nation, and missed commercial opportunities. Overestimating tourism demand, on the other hand, results in an overstock of facilities and services, wasted resources, and low returns on investment (Stekler 2003).

Evidently, the uncertainty created by negative shocks is greater than the uncertainty caused by positive shocks, resulting in an uneven effect on the news cycle. Current theory suggests that individuals are more susceptible to negative signals or news than to positive ones. Tourists usually estimate the prospective loss to be greater than the potential benefit in the event of bad news (Ertuna and Ertuna 2009). Thus, asymmetric demand is both a macroeconomic reality and a tourist phenomenon. The research on economic cycles has shown that the responsiveness of demand to macroeconomic forces can be asymmetrical. Research into the cyclical dynamics of the economy has found that the demand responsiveness in the context of macroeconomic variables may at times be unequal. Specifically, behavioural research indicates that individuals' responses to positive and negative changes in monetary elements, which drive consumer demand, are asymmetrical (Meo et al. 2018). Studies of the oil market have demonstrated that demand reacts differently to changes in income and asymmetric price fluctuations (Gately and Huntington 2002). (Wadud 2015) explains that it is not always possible to reverse the impact of factors such as income, fuel prices, and airfare on the demand for air travel.

Research on tourism growth is becoming increasingly popular to assert that a country's economy grows differently depending on the number of visitors (Sharma and Pal 2020). For instance, (Wang 2012) stated that there is, in fact, a nonlinear association between economic growth and tourism demand. (Shahzad et al. 2017) discovered that tourism activities have various implications on economic expansion. Similarly, exchange rate volatility is nonlinearly related to international trade. (Irandoust 2018) found an asymmetric influence of economic indicators changes on tourist demand. The economic effects have shown that devaluations and gratitude affect the size and sign of tourism demand. The findings have policy ramifications in the sense that a country that relies heavily on its tourism industry may impose restrictions on its use of exchange rate policies to improve its global competitiveness, as these policies may result in currency depreciation, which could lead to a decline in tourism inflows (Irandoust 2019). The contradictory findings could result from the asymmetric influence of the currency rate on tourism demand (Chang and McAleer 2009; Demirel et al. 2013; Yalcin et al. 2021).

Regardless of the approach chosen to study tourism demand, the essential premise underlying all of them is that changes in the values of various economic indicators affect tourism demand (Irandoust 2019). In accordance with the symmetry presumption, if a home currency's deflation increases the number of foreign citizens who vacation

abroad, a currency's appreciation should reduce that number in an equal proportion. Changes in expectations and hypotheses may alter this. Consumers' reactions might be unpredictable when the real exchange rate fluctuates (Iyke and Ho 2020), and speculative attacks tied to a negative shock to exchange rates might enhance the level of uncertainty (Byrne and Davis 2005). A negative exchange rate shock could enhance uncertainty since it would increase the possibility that individuals would anticipate a speculative attack as a result of the shock.

2.3. Studies of Symmetric and Asymmetric Effects across on the News Shocks for Tourism Forecasting

The ways in which news shocks affect the uncertainty about future demand volatility in symmetric and asymmetric ways is a current field of study for academics (Ertuna and Ertuna 2009). A few researchers have examined the uncertainty of international tourist demand in the context of conditionally heteroskedastic models; for example, (Chan et al. 2005) employed three multivariate GARCH models to identify interdependencies between the critical tourism source nations. (Croes and Sr 2005) evaluated the impact of pricing and currency rate on tourist arrivals using the Box–Cox transformation. Using several univariate GARCH models, (Kim and Wong 2006) analysed the log monthly arrival rate of total inbound tourists. Asymmetric impacts on tourist arrivals and the long-term effects of news shocks were of particular concern to them. (Bartolomé et al. 2009) investigated asymmetric effects of equal-sized positive and negative shocks on volatility using three univariate conditional volatility models. (Yap 2012) investigated whether exchange rate fluctuation may increase the uncertainty of international tourist arrivals.

Moreover, (Akar 2012) found that the exchange rate influenced tourism demand. Using a GARCH model, (Vita and Kyaw 2013) determined that fluctuations in the exchange rate impact visitor arrivals. (Agiomirgianakis et al. 2015) studied the detrimental effect of exchange rate volatility (ERV) on tourist arrivals. (Chikobvu and Makoni 2019) employed the ARMA-GARCH and ARMA-EGARCH models to investigate the symmetric and asymmetric influence of good and negative news on foreign visitor arrivals volatility. Tourist volatility was estimated using GARCH, BJR (TARCH), and EGARCH models by (Çelik 2020). Even when there is no leverage effect, volatility asymmetry indicates that negative news's impact does not outweigh the impact of positive news. A reasonably mature tourism destination's worldwide visitor demand and currency rates were simulated using multivariate conditional volatility regressions by (Alleyne et al. 2020). The total arrivals showed asymmetric impacts. (Sharma and Pal 2020) investigated the asymmetric effect of currency rate fluctuation on tourism demand.

2.4. The Economics Index in This Research

Changes to financial markets and financial indexes are attracting the attention of financial analysts and portfolio managers as financial markets become increasingly interdependent (Samanta and Zadeh 2012). Therefore, this study will utilise the top financial news shocks to investigate the symmetric and asymmetric effects on the volatility of tourism demand in Malaysia.

The Kuala Lumpur Composite Index (KLCI) is often considered the Malaysian version of the Dow Jones. In addition, analysts view it as a new, speculative market where investors are more concerned with price fluctuations than with fundamentals. Investors are enticed to better their performance and diversify their portfolios by investing in developing countries due to their high returns. Given that it is a typical Asian growing market and the second-largest non-Japanese Asia market in terms of market capitalisation, a study of this market could have a positive effect on the global investment climate as a whole (Nor and Zawawi 2016; Yao et al. 1999).

When the United States dollar gains "strength" (value) relative to other currencies, the USDX index, which gauges the dollar's value relative to the currencies of U.S. trading partners, rises. Due to this, the USDX index is a good indicator of the relative value of U.S. dollars, as well as a significant indicator of the price of U.S. dollar-denominated

commodities. The majority of international travellers exchange dollars for the local currency (Sun et al. 2017; Tokic 2019).

The Standard & Poor's 500, sometimes known as the S&P500, is a stock market index that tracks the performance of 500 prominent companies that are publicly traded on U.S. stock exchanges. It is a free-float weighted/capitalisation-weighted index that gauges the stock market's performance, with substantial connections between equities and the economy. The S&P500 complies with monetary rules imposed by banks or government increases. The emphasis of the guideline is on assisting with the upkeep of macroeconomic conditions (Verma et al. 2021).

According to the International Energy Agency, as a vital source of energy for industrial output, crude oil is the most important commodity traded on the global market for bulk commodities. Among other things, its price substantially impacts the cost of production, consumption, investment, inflation, and global economic activity. Moreover, crude oil prices tend to move in tandem with geopolitical concerns. They are influenced by other macroeconomic factors, such as changes in monetary policy, fluctuations in exchange rates, and interest rate swings (Hammoudeh et al. 2010).

Gold is also deemed an internationally accepted currency that never loses purchasing power or value, regardless of the state of monetary or banking institutions, which has increased global interest in investing in gold as a risk-hedging instrument. Several studies (Jain and Ghosh 2013; Jayasree and Jyothi 2019; Pukthuanthong and Roll 2011) have found a link between exchange rates and gold price volatility. (Pukthuanthong and Roll 2011) found that when the U.S. dollar (USD) depreciates relative to other currencies, gold prices in USD rise, thereby indicating a relationship between currency appreciation and gold prices in USD (Godil et al. 2020).

Since the aforementioned monetary indexes are intertwined, their volatility impacts the number of tourists and the revenue of nations dependent on tourism.

2.5. News Shocks for Malaysia

Annual foreign tourist arrivals to Malaysia display significant volatility indicators and are likely to be influenced by many variables. The Malaysian Year of Festivals in 2015 was one of the numerous significant events in Malaysia's recent history, alongside the Visit Malaysia Years in 1990, 1994, 2000, 2007, and 2014. This is helpful information for arriving tourists, as Malaysia has become one of the world's most popular tourist destinations and a popular Muslim-friendly vacation destination. After the 2003 SARS outbreak, adverse events declined significantly, such as the number of visitors visiting Asia. Contributing reasons include, for instance, the global economic crisis and severe internal events in Malaysia, such as the worst flood in 30 years, which ravaged many states in early 2015. The earthquakes that struck Ranau, Sabah, in the middle of 2015, as well as a travel experience restriction for the coastal parts of Sabah's southeastern coast, coupled with the remaining impacts of the MH370 and M17 tragedies, Sabah's decline in tourism, may have been caused by a combination of these causes. Several pieces of news have the ability to affect, either directly or indirectly, the number of tourists visiting Malaysia each month.

3. Model Description

3.1. Volatility Models with Financial News Shocks

The generalised autoregressive conditional heteroscedasticity (GARCH), the exponential generalised autoregressive conditional heteroscedasticity (EGARCH), and the generalised joint autoregressive conditional heteroscedasticity (GJRGARCH) models were employed in order to estimate the effects of a financial news shock on the monthly tourism demand in Malaysia. Initially published by (Engle 1982), who also introduced the ARCH model, it was the work that laid the foundation for volatility theory. Bollerslev then presented the GARCH model in 1986, having contributed to the concept's continuous development. The refinement of the theory led to the development of the EGARCH and GJRGARCH models, which are more intricate than their predecessors. These models make

it possible for an asymmetrical relationship between the effect of news broadcast and volatility. It has been demonstrated that a short lag, such as that observed in the GARCH model (1, 1), is sufficient for describing the shifting of the variance over long sample periods (Chong et al. 1999; Franses and Van Dijk 1996; Poon and Granger 2003). In light of the aforementioned considerations, the research investigation opts to apply the EGARCH and GJRGARCH models with the (1, 1) specification. This research studied the impacts of financial news shocks on the GARCH, EGARCH, and GJRGARCH models to determine whether these models might be used to anticipate changes in Malaysian tourism demand. The three variance models were then combined with five financial news shocks: KLCI (DXY), S&P500, Crude Oil (CO), and Gold Price (GP) for each variance model.

The GARCH model, which Bollerslev (1986) is credited with creating, is one of the most used models for measuring and predicting volatility. This model is also a weighted average of previously squared residuals, but its weights decline and never reach zero. It provides simple models that are straightforward to estimate and, even in its most basic version, has proven to be very accurate at predicting conditional variances. This model permits and accounts for the conditional variance of the variable to become reliant on any past delays, and it is also capable of capturing information and news included within the historical variance values in the tourism forecasting area. The variance model is known as GARCH (1,1) with financial news shocks is described as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \theta_1 KLCI \tag{1}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \varphi_1 DXY \tag{2}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \zeta_1 \text{S\&P500} \tag{3}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \lambda_1 CO \tag{4}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \mu_1 GP \tag{5}$$

This model is built to enforce a non-negativity requirement for the coefficients α and β to ensure that the model consistently provides an output with a variance value greater than one and a coefficient value greater than one. Despite its extensive use and overall success, the GARCH model shockingly does not account for the possibility of asymmetric volatility. It is crucial to note that this constraint has been somewhat mitigated and overcome by the development of more flexible volatility treatments that account for the volatility's uneven response to both positive and negative shocks (French et al. 1987). In these models' equations, the value of the conditional variance is usually determined not by the sign of the lagged residuals but by their magnitude and size. As a result, this study paper also adopted and applied additional GARCH family models, as it is the most applicable and acceptable model for evaluating the accuracy of forecasting in the setting of tourism demand volatility.

A potential issue with applying the model of Equation (1) to data on tourism demand is that it assumes that the effects of positive and negative shocks are equivalent or symmetric. This is because the conditional variance in these equations depends on the size, not the sign, of the lagged residuals. The notion that a negative tourism movement shock could increase volatility more than a positive tourism movement shock of the same magnitude warrants further study (French et al. 1987). Consequently, to address and correct these shortcomings and weaknesses of the GARCH models, (Nelson 1991) devised the EGARCH model. Using financial news shocks, the EGARCH (1,1) variance model with financial news shocks looks like this:

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \phi_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) + \theta_1 KLCI \tag{6}$$

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \phi_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) + \varphi_1 DXY \tag{7}$$

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \phi_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) + \zeta_1 \text{S\&P500} \tag{8}$$

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \phi_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) + \lambda_1 CO \tag{9}$$

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \phi_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln\left(\sigma_{t-1}^2\right) + \mu_1 GP \tag{10}$$

If $\phi_1 = 0$, then the variance is asymmetric in the situation. The conditional variance can also be described in terms of the left-hand logarithm. Due to the assumption that the leverage effect is exponential rather than quadratic in its characteristic, the conditional variance predictions are assumed to be nonnegative. When employing the EGARCH model, the conditional variance σ_t^2 is an exponential function. Hence there is no need to constrain the parameters. Because of this, EGARCH has become a widely used option for a wide variety of applications (Coshall 2009).

The GJRGARCH model, which was discussed by (Glosten et al. 1993), is a popular adaptation that provides the asymmetry necessary to find the "leverage effect." The following is the formula for the GJRGARCH (1,1) variance model with financial news shocks:

$$\sigma_t^2 = \omega + (1 - I[\varepsilon_{t-1} > 0])\alpha_1 \varepsilon_{t-1}^2 + (I[\varepsilon_{t-1} > 0])\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad + \theta_1 KLCI \tag{11}$$

$$\sigma_t^2 = \omega + (1 - I[\varepsilon_{t-1} > 0])\alpha_1 \varepsilon_{t-1}^2 + (I[\varepsilon_{t-1} > 0])\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad + \varphi_1 DXY \tag{12}$$

$$\sigma_t^2 = \omega + (1 - I[\varepsilon_{t-1} > 0])\alpha_1 \varepsilon_{t-1}^2 + (I[\varepsilon_{t-1} > 0])\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad + \zeta_1 \mathrm{SP500} \tag{13}$$

$$\sigma_t^2 = \omega + (1 - I[\varepsilon_{t-1} > 0])\alpha_1 \varepsilon_{t-1}^2 + (I[\varepsilon_{t-1} > 0])\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad + \lambda_1 CO \tag{14}$$

$$\sigma_t^2 = \omega + (1 - I[\varepsilon_{t-1} > 0])\alpha_1 \varepsilon_{t-1}^2 + (I[\varepsilon_{t-1} > 0])\gamma_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad + \mu_1 GP \tag{15}$$

where $I[\varepsilon_{t-1} > 0]$, this represents the indicator function, which yields 1, if $\varepsilon_{t-1} > 0$ and is 0 otherwise. Therefore, if $\varepsilon_{t-1} > 0$, it indicates that the tourist environment is going to be affected negatively by the news, but if it is going to be affected positively by the news, it indicates that the tourism environment is going to be affected positively by the news. Thus, according to these equations, the influence of positive news on the conditional variance is captured by the symbol α, whilst the effect of negative news on the conditional variance is captured by the symbol $\alpha + \gamma$. This indicates that the leverage effect is present if $\gamma > 0$, and the asymmetry impact is present if $\gamma \neq 0$.

3.2. Evaluation Criterion

The selection of a forecasting model is a difficult procedure. The effectiveness of the prediction is highly dependent on recognising and accounting for any forecasting errors. The purpose is to maximise profit by choosing the optimal feasible rate for the forecasts, which can be achieved by maximising precision. Because there are numerous potential prediction models, each with its own distinct set of criteria, traits, and requirements, there is no one approach to anticipate and account for forecasting errors while assessing prediction accuracy (Song and Li 2008). In this study, the accuracy of the forecast was assessed using a variety of methodologies. In this study, the mean absolute error (MAE), root mean squared error (RMSE), and Theil-U were employed as components of the evaluation criteria for analysing forecasting errors.

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| \hat{\sigma}_t^2 - \sigma_t^2 \right| \tag{16}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2} \tag{17}$$

$$Theil - U = \frac{\sum_{t=1}^{n} \left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2}{\sum_{t=1}^{n} \left(\left(\hat{\sigma}_t^2\right)^{BM} - \sigma_t^2\right)^2} \tag{18}$$

where n is the sample size, $\hat{\sigma}_t^2$ represents the forecasting value, σ_t^2 indicates the actual value, and $(\hat{\sigma}_t^2)^{BM}$ is the benchmark forecast (Poon and Granger 2003). The term "average model performance error" or "mean absolute error" (MAE) relates to this concept. The most popular applications for this statistic include criteria evaluations as well as comparisons of the average model-performance error (Willmott and Matsuura 2005). Root mean square error (RMSE) is also used to evaluate and examine the mistakes of different estimation technique techniques for the same set of data predictions and their corresponding outputs. This evaluation and analysis are conducted with the same data set (Hyndman and Koehler 2006). Additionally, Theil-U is resistant to the translation of any scalar; therefore, it would be more appropriate and useful to examine and assess which method employed in this inquiry is regarded as the most accurate in order to produce more accurate forecasts (Poon and Granger 2003).

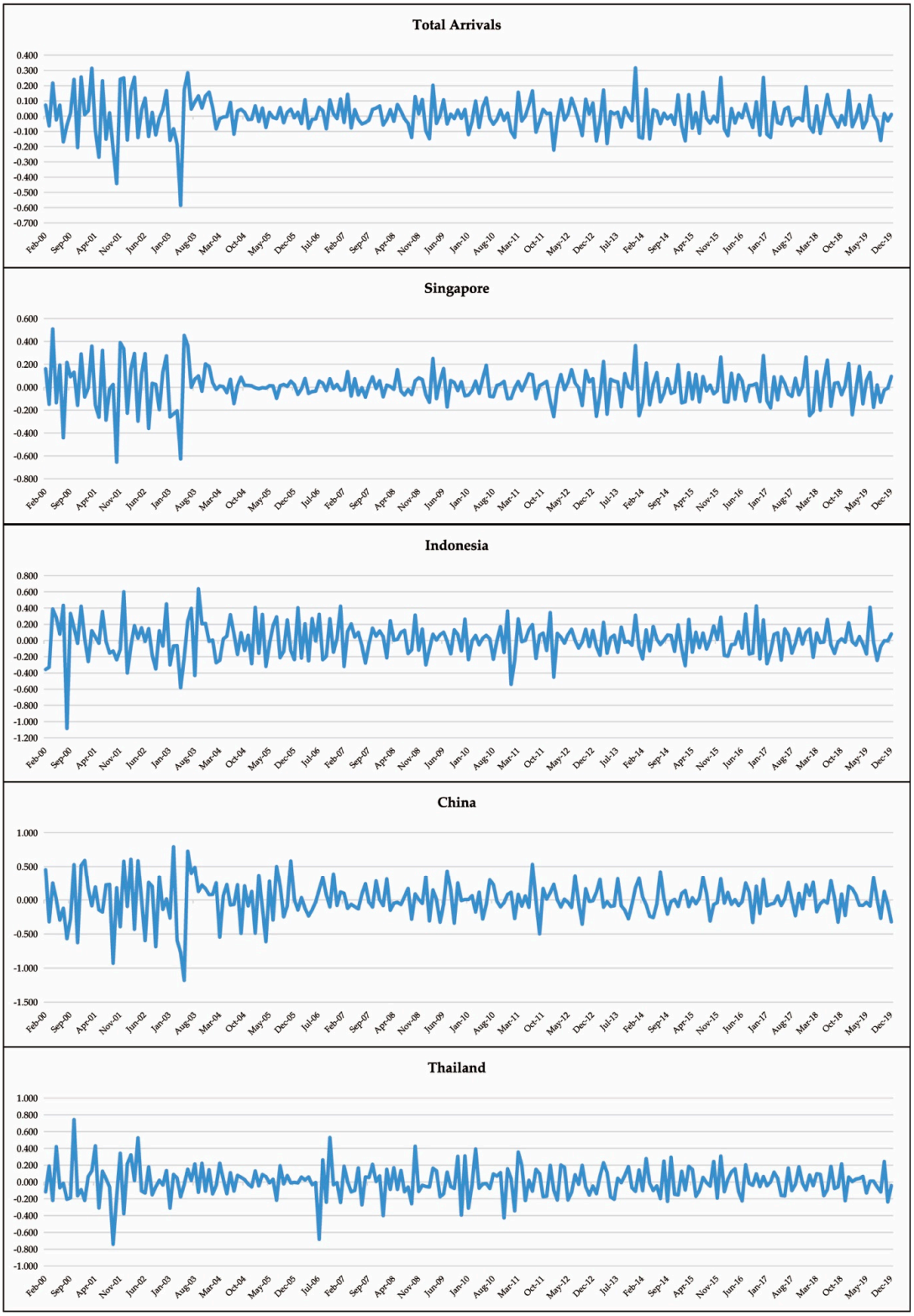
4. Data Description

For the modelling method, Tourism Malaysia Corporate's database was applied to collect monthly data on the quantity of inbound tourism demand to Malaysia. The Ministry of Tourism and Culture of Malaysia compiles statistics from different sources pertaining to tourism. For instance, the statistics compiled by the Malaysian Immigration Department regarding inbound tourists. We collected the database for a total of 54 countries/regions having tourist arrivals from all continents. Africa, the Americas, Asia, Europe, and the Pacific each contain 4, 3, 28, 17, and 2 countries/regions, respectively, for the inbound tourist arrivals data in Malaysia.

Importantly, our dataset contains numerous noises and outliers. Typically, an outlier is an observation that deviates from the mean by three times the standard deviation. In addition, outliers can result in model misspecification, biased parameter estimates, and erroneous analytic outcomes. The intricacy of our information and the volatile nature of tourism allows us to anticipate future demand using historical data. Since the data at our disposal cover only a few years in the past, namely, the data volume of some countries or regions only relates to the last five years or fewer years, and only yearly and quarterly, such as Brazil (2012–2016), Kazakhstan (2012–2019), Poland (2002–2019), Italy (2012–2019), Finland (2015) and so forth. They give insufficient data for computing standard deviations. Moreover, only 28 of the total 54 countries/regions satisfy the data time span of 2000 to 2019. However, the total number of visitors coming to Malaysia is too low to facilitate modelling and improve forecast accuracy due to missing data and outliers. In the absence of sufficient data to employ more precise statistical methods, and in order to deal with the high variability of demand whenever special news shocks occur in different inbound countries, we decided, following a preliminary analysis, to conduct a data stability test on the tourist arrivals used for forecasting purposes in order to eliminate outliers. Thus, to conduct this research, the top and most significant inbound tourism nations in terms of visitor arrivals and spending worldwide were selected: Singapore, Indonesia, China, Thailand, South Korea, Japan, Australia, the UK, and the USA. They accounted for a total of 81.31% of 2019's total arrivals, making them the most significant sources. Similarly, when we collected data for other financial indexes, they underwent the aforementioned data filtering procedure. The remaining monthly financial news shocks were obtained from Yahoo Finance and included the Kuala Lumpur Composite Index (KLCI), DXY, S&P500, crude oil (CO), and gold price (GP).

From January 2000 to December 2019, 239 observations were made regarding the above series. For purposes of estimate and modelling, the first 179 data points were used. The prediction ability of the out-of-sample data was examined using sixty additional observations. The majority of this paper is devoted to forecasting the future. Before proceeding with the creation and evaluation of the optimal model, (Engle and Granger 1987) indicated that a stationarity test must be done. This is due to the fact that picking the incorrect data transformations might lead to erroneous outcomes, which in turn can result in incorrect data interpretation. Before developing and evaluating the optimal model, it is necessary

to evaluate whether or not the data are stationary. Figure 2 used the natural logarithm of Malaysia's tourist demand as raw data to assess and investigate the volatility models included in this study's conclusions. Figure 2 demonstrates a greater degree of stationarity. Before developing and evaluating the optimal model, it is necessary to evaluate whether or not the data are stationary.



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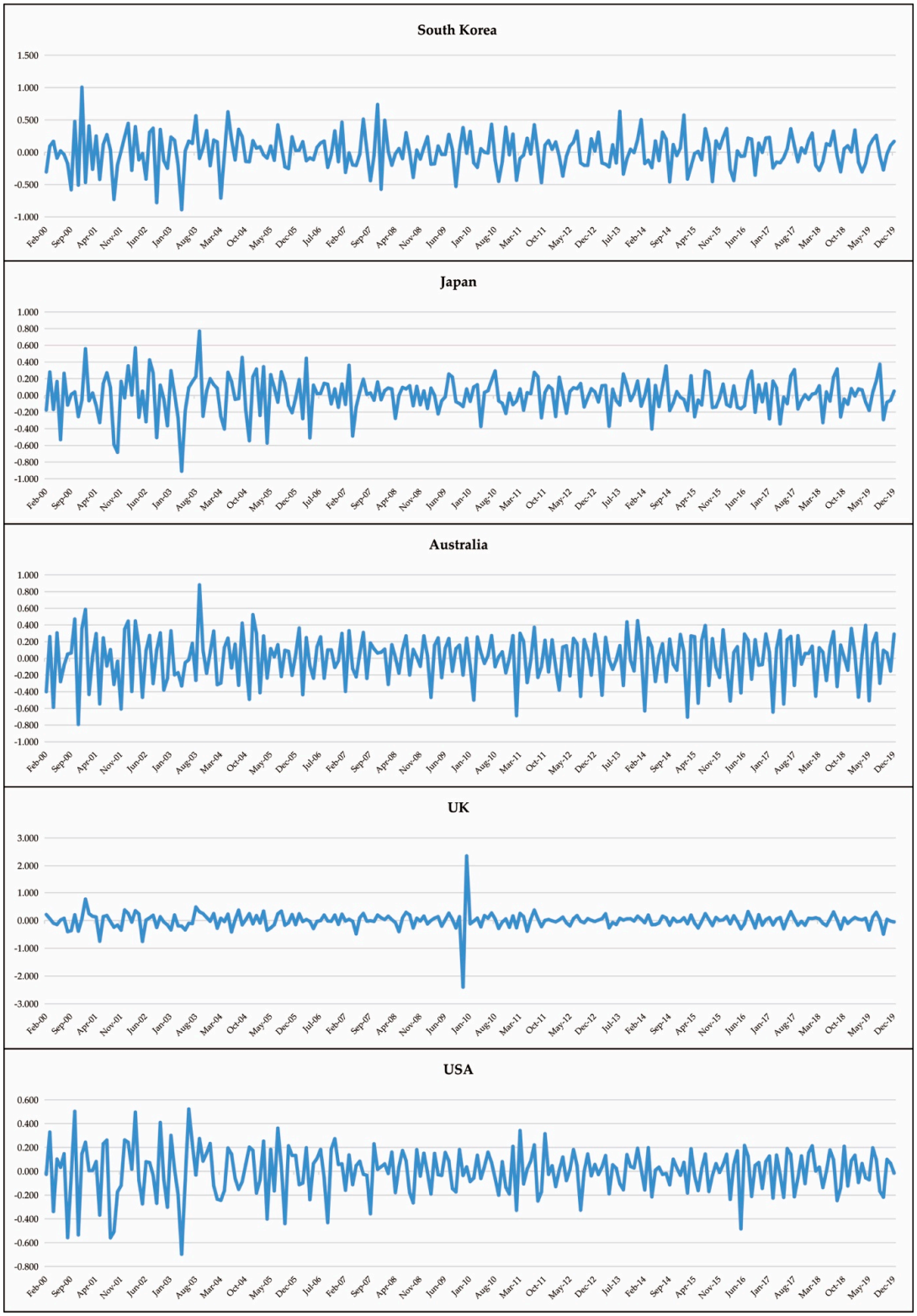

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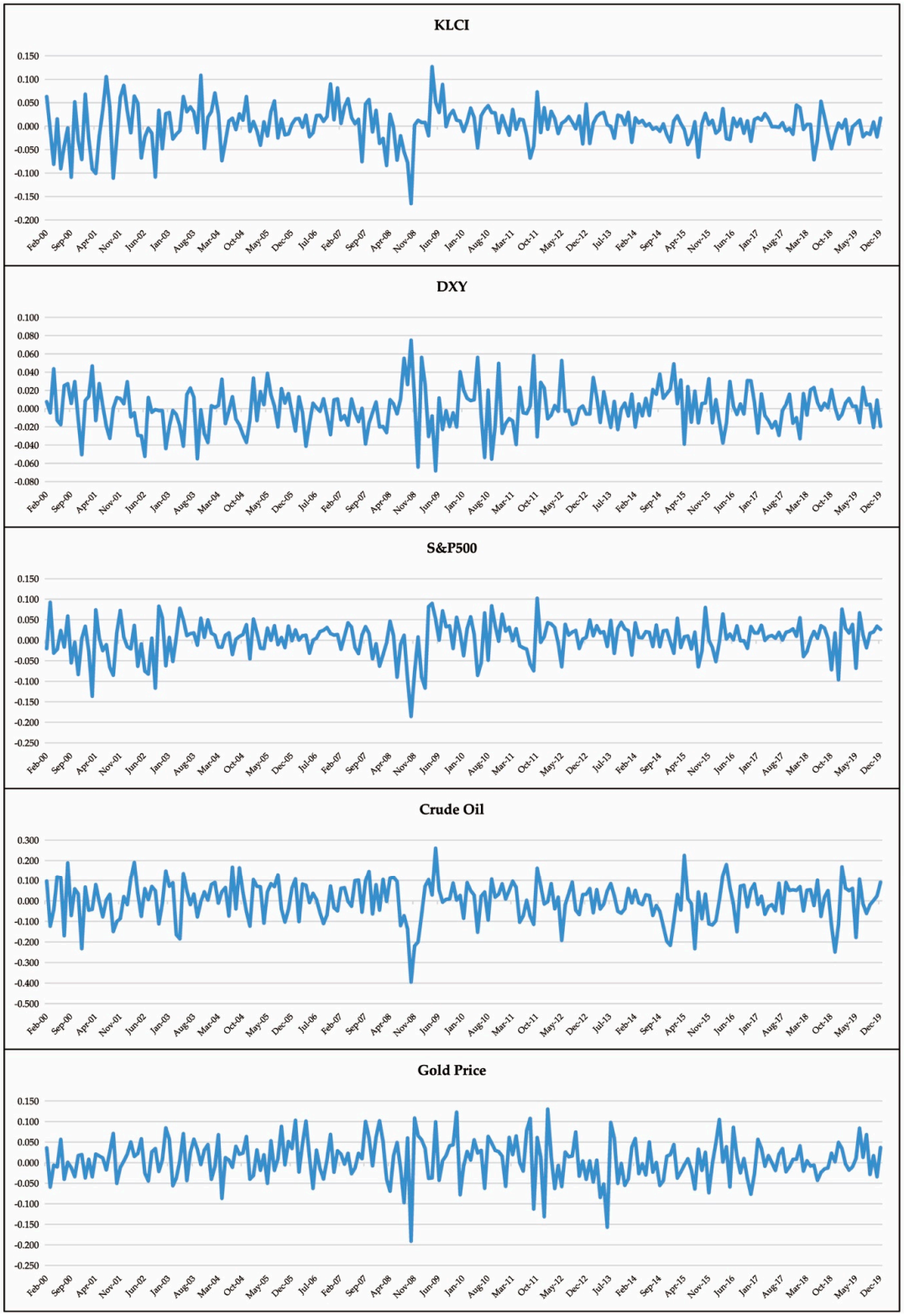


Figure 2. Monthly volatility for tourist arrivals into Malaysia and five financial news shocks.

5. Research Process

The study employed the monthly log difference of data on tourism demand from Figure 3 for data analysis. First, statistics on arrivals into Malaysia from a total of 54 countries/regions on every continent were retrieved. The second stage is to analyse the gathered

data for outliers, missing data, and insufficient time range in order to obtain more accurate modelling and prediction outcomes. A total of 26 countries/regions failed the initial examination, while 28 countries/regions were included in the study. The data filtering process was repeated in the specified nations in the third stage. The sub-steps include, (1) comparing the monthly visitor data from 28 nations or regions. This is because the number of visitors entering Malaysia from certain nations is extremely low, even close to ten, and such data is insufficient for producing more accurate modelling and prediction results. (2) For modelling, audited data must be translated into a specific range (log return) because some data are too large. (3) An improved Dickey–Fuller (ADF) test (Lim and McAleer 2000) and a Philips–Perron (P.P.) test (Phillips and Perron 1988) were used to detect and evaluate the presence of a unit root test and the consistency of the log difference of time series for volatility analysis and these tests were used independently of every dataset. On the basis of the aforementioned selection criteria, nine nations or regions were ultimately chosen for this study. In the fourth step, we used the nine identified inbound tourism market data in Malaysia to conduct cluster analysis and structural fault analysis in order to gain a clearer and more comprehensive understanding of whether the data is affected by different news shocks at different times. Importantly, we employed the conditional mean equation to investigate the monthly seasonality and the link between the series to create the residual values for the variance equations. The next thing that needed to be performed was a statistical analysis of εt to determine whether it met the criteria for modelling and whether or not it had attained the standard. Through diagnostic testing of the residuals t values in the conditional variance equations, the monthly Malaysian tourism demand volatility models with five financial news shocks were evaluated in the fifth stage. These tests were conducted to determine whether or not these models exist. The variance equations and three approaches to financial news shocks utilised in this study were stated from the news impact curve for the symmetric and asymmetric impacts analysis, followed by the evaluation of several models of volatility by subjecting them to news shocks to determine which model provides the most accurate estimate when applied to the within-sample data of the international tourism demand volatility in Malaysia within the sixth step. In the seventh step, forecasting evaluation criteria (MAE, RMSE, and Theil-U) are applied to determine which of the models is the best forecasting model for the volatility forecast of international tourism demand and which has the most significant news shocks impact on the tourist arrivals into Malaysia between the in-sample evaluation and out-of-sample forecasting procedure. Finally, a summary was compiled, and the findings yielded in this study were assessed if they achieved the study's purpose.

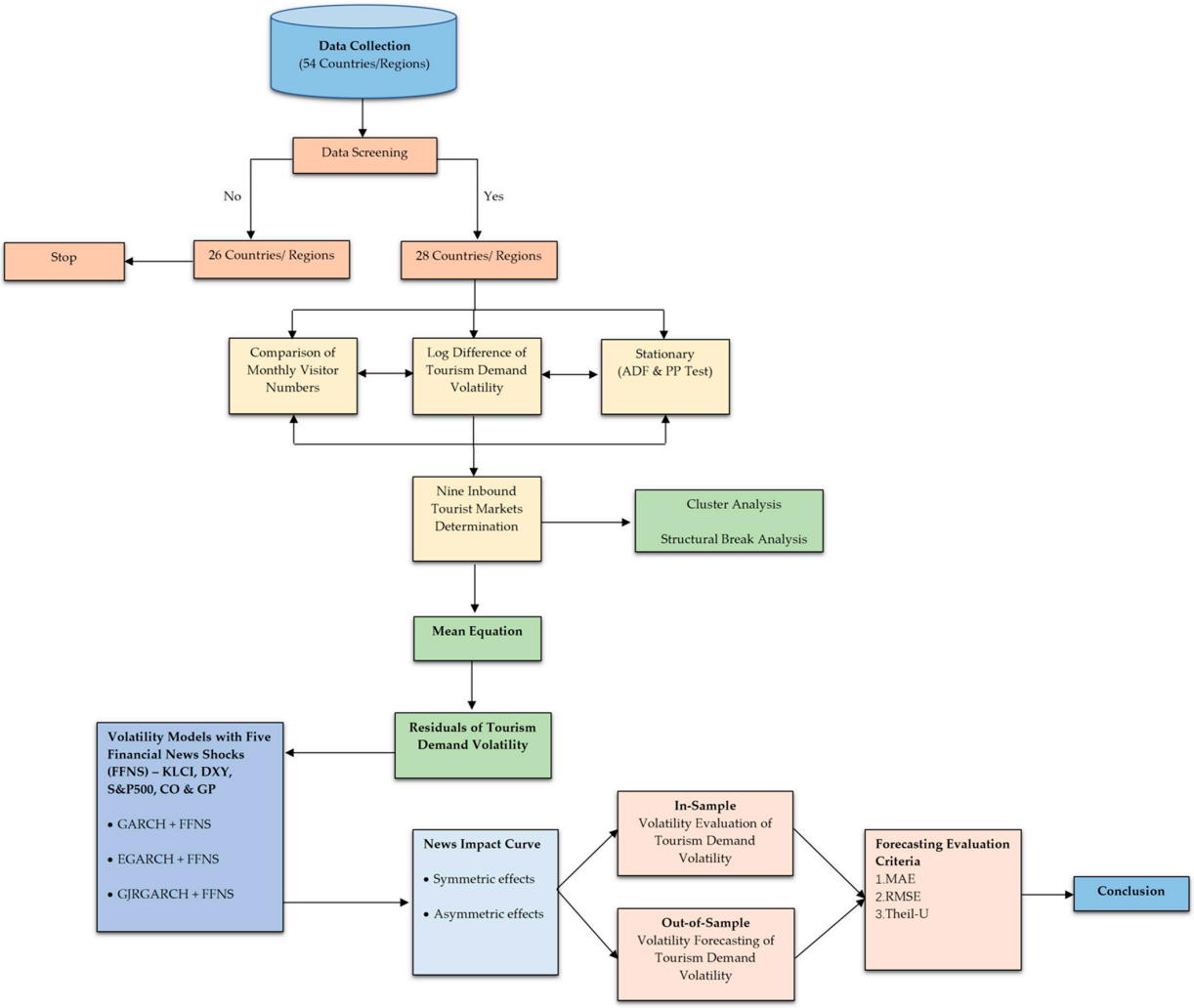


Figure 3. Research Framework.

6. Empirical Results

6.1. Cluster Analysis

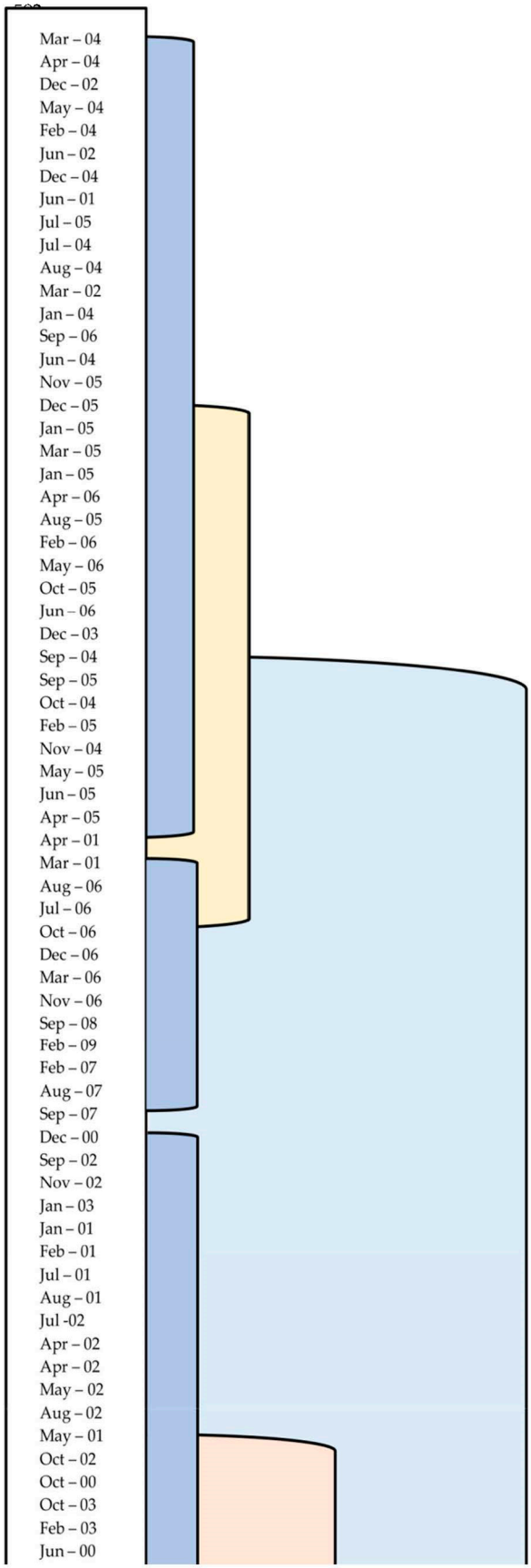
The objective of clustering is to detect structure in an unlabelled data set by objectively grouping the data into homogenous groups with minimum within-group-object similarity and maximum between-group-object dissimilarity (Liao 2005). Among them, visualising data by the hierarchical cluster analysis and plotting dendrograms (tree diagrams) is an effective method reviewed and discussed in various existing research works (Meilă 2007; Lemenkova 2020). Hierarchical clustering aims at grouping data by attribute similarities. The hierarchical cluster analysis was performed using the "Analyse/Classify/Hierarchical Cluster" module by the SPSS Statistics. Notably, time series clustering requires a clustering technique or procedure to generate clusters from a set of unlabelled data items, and the choice of clustering algorithm depends on the type of data available as well as the specific goal and application. As far as time-series data are concerned, distinctions can be made as to whether the data are discrete-valued or real-valued, uniformly or non-uniformly sampled, univariate or multivariate, and whether data series are of equal or unequal length.

Hierarchical clustering analysis was performed on the monthly inflow of Malaysian visitors and five financial news shocks in this article to determine whether or not they are affected by different news shocks at distinct clustering times and why they gather, as depicted in Figures 4 and 5, Tables 1 and 2 (see below). Since the same arrivals or financial metrics were directly affected by the same news, they had to be grouped together. Using a six-colour coding technique, Figure 4 displays the flow of tourists from nine countries

entering Malaysia from January 2000 to December 2019 (six categories). Clusters appear more frequently in the following time periods: dark purple, pink, and light blue clusters are mirrored in the year's clusters, 2001, 2002, and 2003; the dark purple, light yellow, and light blue groups comprised the 2003, 2004 and 2005 clusters; the years 2007–2009 are represented by the dark purple, light yellow, and pink clusters; the dark purple, light yellow, pink, and green gather in the years' clusters 2015, 2016, and 2017. According to a dendrogram, Table 1 displays the amounts of inbound tourists from each country clustered into several groups. Regarding tourism, each cluster receives a varying number of visitors at any moment. Each of China, Japan, and the USA had a greater maximum population in Cluster 1 than in any other cluster. Similar to Cluster 2, Clusters 4 and 5 have the most visitors from Thailand, Indonesia, Australia, the Republic of Korea, and the UK.

Table 1. Clusters descriptive statistics of tourist arrivals into Malaysia.

Cluster Number of Case		N	Minimum	Maximum	Mean	Std. Deviation
1	Total Arrivals	51	2081,354	2,415,097	2,227,009	85,578
	Singapore	51	846,951	1,278,027	1,108,604	92,942
	Indonesia	51	173,753	381,239	243,610	46,594
	China	51	58,351	310,380	156,990	60,048
	Thailand	51	86,592	172,459	127,637	24,465
	South Korea	51	14,943	69,225	34,720	14,392
	Japan	51	24,533	58,754	37,435	7356
	Australia	51	21,285	58,971	40,260	10,035
	UK	51	25,325	46,780	34,139	4435
	USA	51	13,985	27,462	20,286	2849
2	Total Arrivals	11	2,342,187	2,806,565	2,495,849	136,252
	Singapore	11	1,203,449	1543,174	1,301,514	89,685
	Indonesia	11	216,701	334,630	261,168	40,591
	China	11	96,181	213,822	154,591	39,143
	Thailand	11	91,049	160,410	117,279	23,671
	South Korea	11	21,920	51,036	33,304	9732
	Japan	11	32,304	56,369	44,189	7789
	Australia	11	32,773	70,801	49,871	10,903
	UK	11	27,275	46,269	36,553	6358
	USA	11	16,950	26,218	21,871	3046
3	Total Arrivals	38	456,374	1,149,987	900,403	169,680
	Singapore	38	205,065	626,435	487,537	104,575
	Indonesia	38	23,998	84,162	52,137	16,327
	China	38	6016	82,315	42,946	19,240
	Thailand	38	43,038	126,866	84,331	22,183
	South Korea	38	1816	8249	5018	1772
	Japan	38	7242	50,594	28,938	12,396
	Australia	38	6801	32,256	16,469	6175
	UK	38	5051	33,888	17,083	7127
	USA	38	4554	21,094	11,882	4297
4	Total Arrivals	46	1,135,493	1,564,286	1,357,535	99,044
	Singapore	46	611,051	859,688	785,359	54,618
	Indonesia	46	50,203	138,191	80,478	18,547
	China	46	20,818	82,893	47,011	13,646
	Thailand	46	74,985	193,851	138,808	29,639
	South Korea	46	3278	19,820	10,817	4588
	Japan	46	16,212	45,482	28,646	6753
	Australia	46	11,485	29,981	19,959	4461
	UK	46	12,879	36,678	19,834	4817
	USA	46	8746	19,727	13,221	2711
5	Total Arrivals	58	1,924,129	2,253,534	2,047,351	69,711
	Singapore	58	738,951	1,157,094	971,908	108,520
	Indonesia	58	157,957	314,855	224,929	35,710
	China	58	71,566	303,867	164,800	64,350
	Thailand	58	80,666	184,168	132,760	27,533
	South Korea	58	13,743	74,964	33,184	14,828
	Japan	58	26,139	46,797	36,175	5430
	Australia	58	20,245	56,601	36,157	9165
	UK	58	3522	49,421	31,684	6590
	USA	58	13,771	23,886	19,387	2262
6	Total Arrivals	36	1,599,418	1,928,082	1,798,071	99,228
	Singapore	36	801,442	1,038,004	915,810	64,895
	Indonesia	36	115,446	245,604	173,419	30,862
	China	36	49,852	142,997	83,475	22,037
	Thailand	36	85,824	162,208	123,570	19,442
	South Korea	36	12,814	29,740	21,381	4964
	Japan	36	23,293	43,555	31,993	5082
	Australia	36	19,924	63,796	35,062	9804
	UK	36	15,794	39,505	28,686	5667
	USA	36	12,553	23,080	17,564	1889



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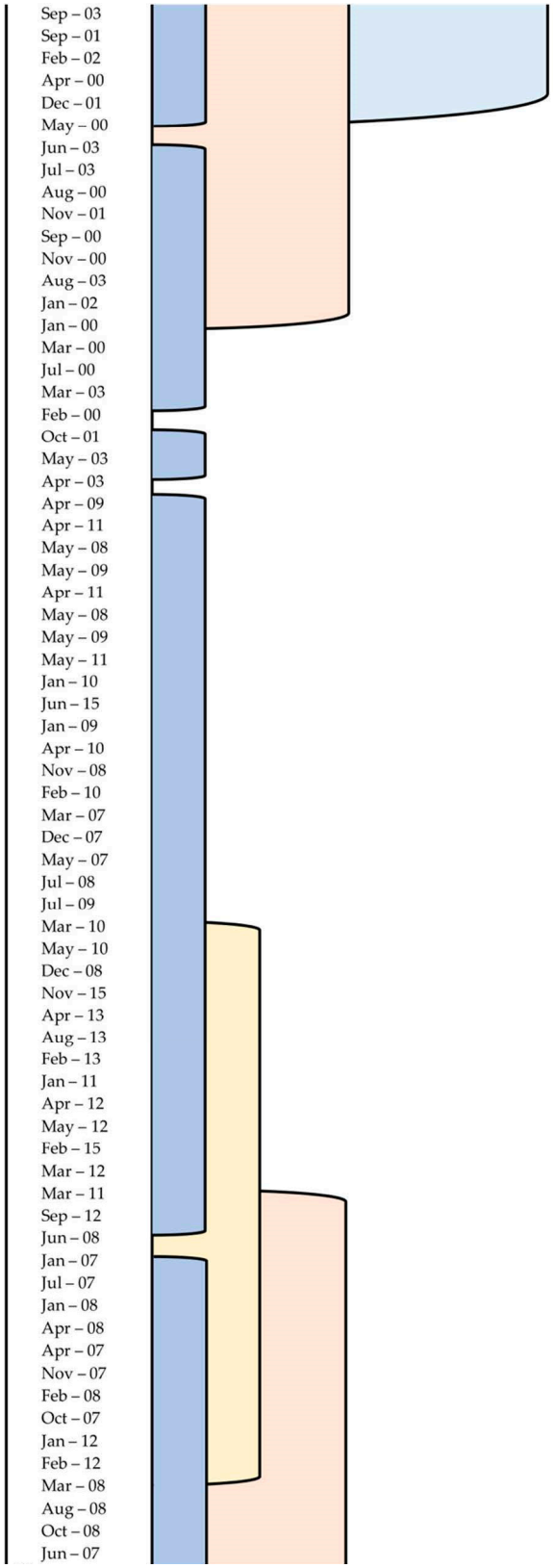

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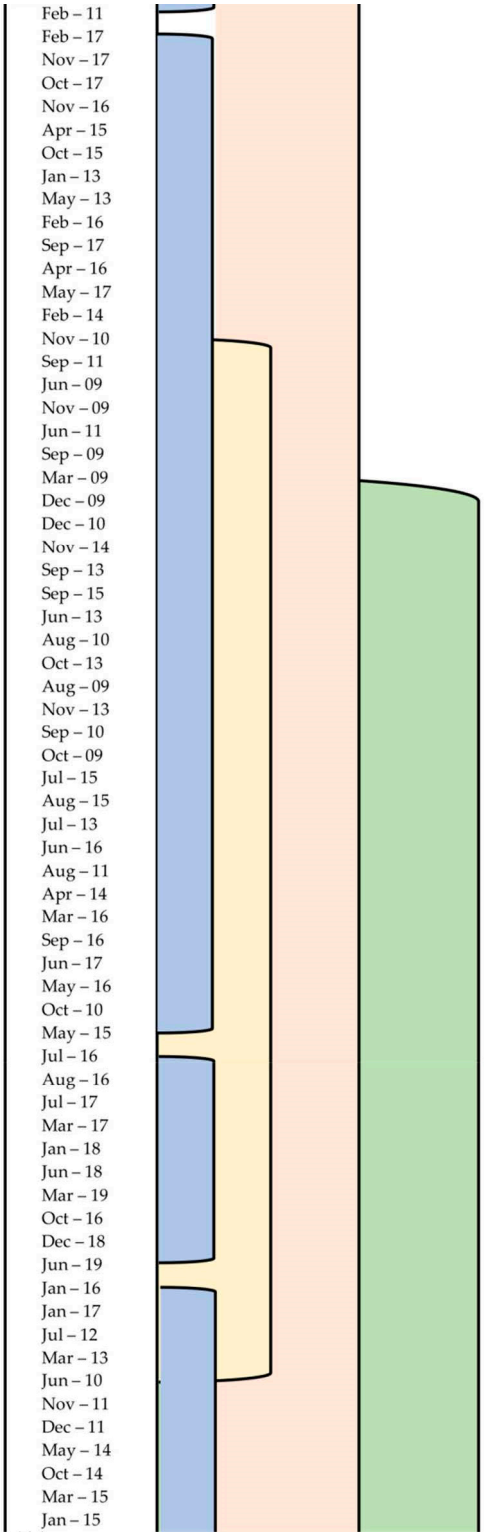

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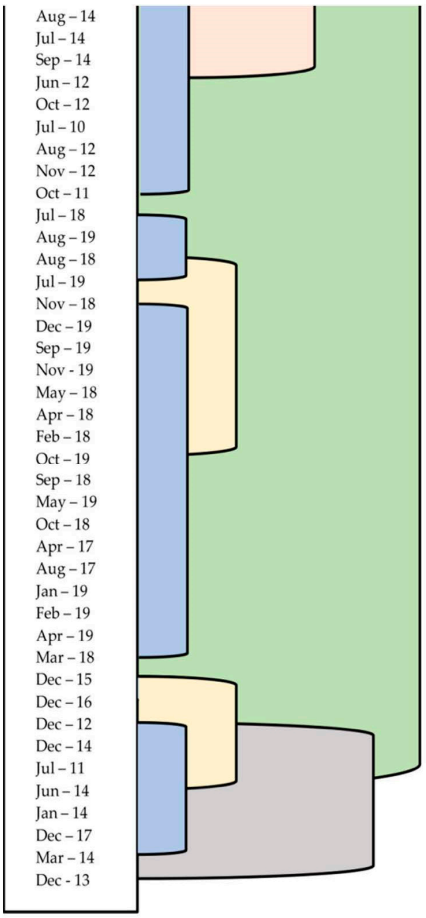
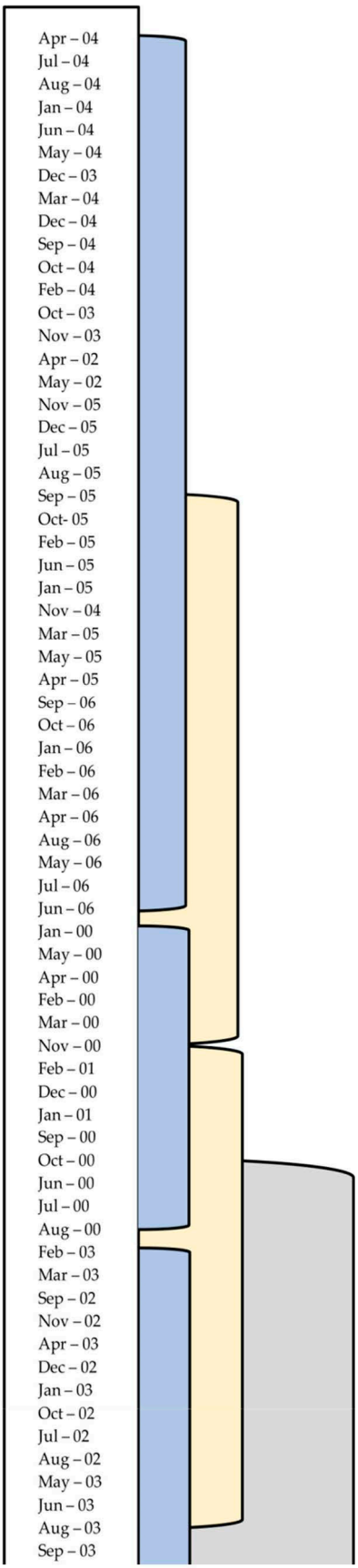


Figure 4. Tourist arrivals dendrogram using average linkage (between groups).

Table 2. Clusters descriptive statistics of five financial news shocks.

Average Linkage (Between Groups)		N	Minimum	Maximum	Mean	Std. Deviation
1	KLCI	82	573	988	794.9634	117.2299
	DXY	82	80.85	120.24	99.2131	12.3764
	S&P500	82	815.28	1517.68	1169.2202	165.90727
	CO	82	19.44	74.4	39.1883	15.70206
	GP	82	257.7	653	379.7537	108.17025
2	KLCI	23	1019	1445	1265.0435	118.62526
	DXY	23	71.8	84.61	78.2876	4.26286
	S&P500	23	1166.36	1549.38	1407.2822	96.47426
	CO	23	58.14	140	88.6813	24.04428
	GP	23	632	971.5	777.3913	118.78382
3	KLCI	23	864	1422	1142.1739	189.45488
	DXY	23	74.79	88.17	81.7068	3.83486
	S&P500	23	735.09	1186.69	998.0861	120.74886
	CO	23	41.68	86.15	67.6891	13.25587
	GP	23	730.8	1246	1023.3957	142.45215
4	KLCI	31	1387	1689	1559.4839	73.44062
	DXY	31	72.93	83.04	78.6834	2.80353
	S&P500	31	1131.42	1569.19	1333.9268	105.86534
	CO	31	79.2	113.93	94.0742	8.38918
	GP	31	1307	1813.5	1588.4903	141.54319
5	KLCI	46	1613	1883	1748.5217	85.54576
	DXY	46	79.47	102.21	90.351	7.87088
	S&P500	46	1597.57	2278.87	1972.8365	174.89798
	CO	46	33.62	107.65	68.6385	25.81199
	GP	46	1060	1469	1237.7696	88.77079
6	KLCI	35	1562	1870	1720.9429	84.26846
	DXY	35	89.13	101.12	95.6054	2.91249
	S&P500	35	2362.72	3227.57	2726.2643	225.18085
	CO	35	45.41	74.15	58.0206	7.82199
	GP	35	1187.3	1528.4	1314.5686	91.83536



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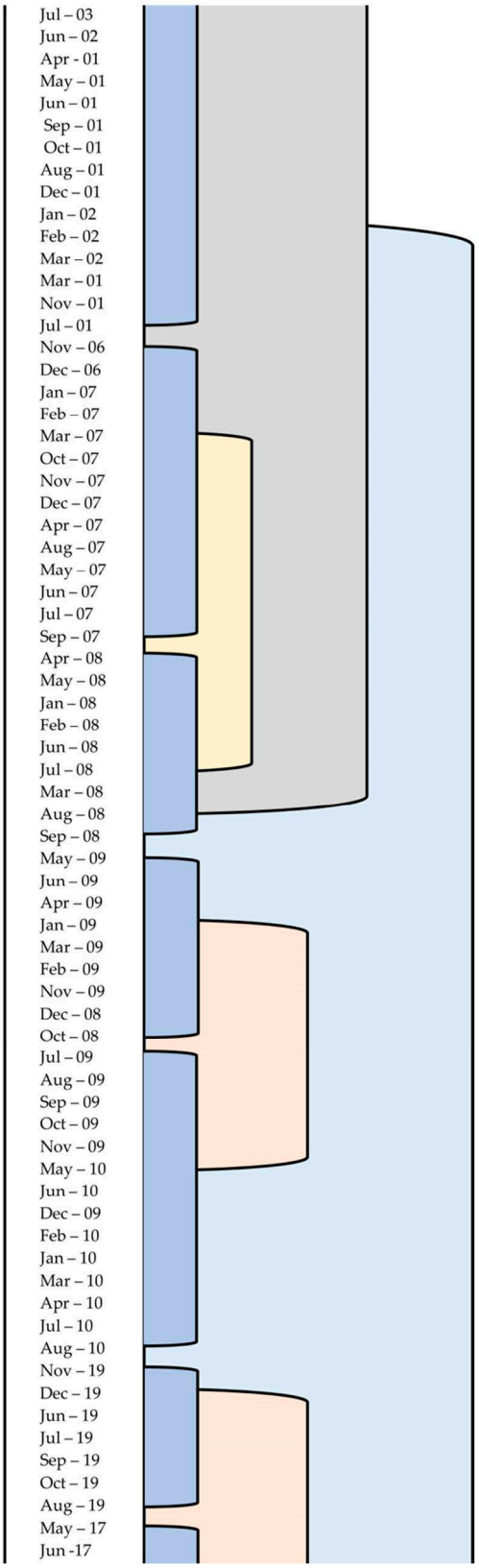

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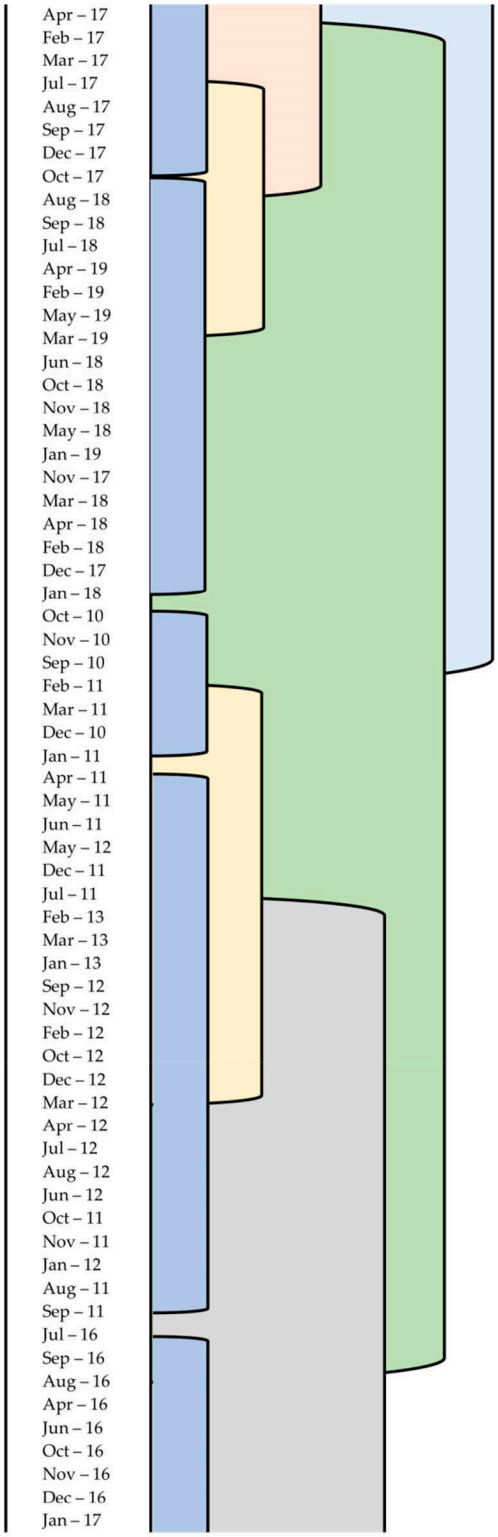

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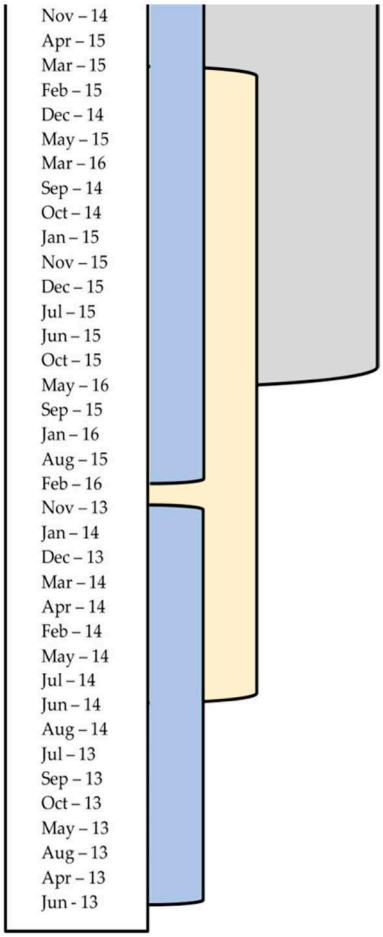


Figure 5. Financial indexes dendrogram using average linkage (between groups).

In a similar fashion, Figure 5 depicts five financial indices over six distinct time periods. The years 2001–2003 are represented by the spectrum's dark purple, pale yellow, and grey. There are groups for 2007, 2008, and 2009 represented in varying tones of dark purple, pale yellow, and grey. Years 2012 and 2013 were the most prevalent years for the buff, grey, and green clusters. In 2014, there were dark purple, yellow, and grey groupings for each of the three cohorts. Except for grey, groups from 2017 to 2019 are represented in all but one of their colour groupings. In Table 2, DXY in Cluster 1, CO in Cluster 2, GP in Cluster 3, KLCI in Cluster 5, and S&P500 in Cluster 6 exhibited the highest values of tourist arrivals, respectively. Consequently, the various financial indices will exhibit distinct movements in their respective groupings throughout time. The preceding data will be analysed in conjunction with the subsequent section on structural breaks.

6.2. Structural Break Analysis

It is fascinating to observe how effectively classification analysis interprets cluster variance in tourism demand volatility over different time periods and how shocks influence key source countries on an individual basis. We will employ structural break analysis in conjunction with the cluster data analysis. A structural break occurs when an abrupt change occurs in a time series. By exploiting the structural break measure (Bai and Perron 1998), (Cró and Martins 2017) found that tourism catastrophes and crises are generally compatible with cracks' dates. This strategy allows us to solve a void in the tourism industry regarding the appropriate scheduling of negative shocks in foreign tourist arrivals in the context of the current economic crisis. We assess tourist arrivals into Malaysia in this manner because force majeures, such as financial crises, are renowned for producing systemic splits in time series and rendering mean and variance unstable.

Table 3 displays the results of the test for structural cracks in Malaysian tourist arrivals and financial indices. Except for South Korea and the S&P500, the most notable aspect of this table is that almost all countries considered were significantly affected by a structural rupture in 2003, which coincided with the outbreak of SARS. As shown in Figure 2, the four nations with the highest demand for Malaysian tourism in 2003 experienced the same turbulent SARS-related period. The year 2003 was particularly turbulent for Japan, with a 7.0 magnitude earthquake striking the main island in May and an 8.3 magnitude earthquake striking in September. In 2001, they exhibited a hostile response to the September 11th tragedy in the USA. Various countries also saw significant events in 2006, including the military coup in Thailand and the murder case in Malaysia, among others. In 2007, the USA real estate bubble burst, and the subprime mortgage storm emerged as well as the USA financial industry suffered greatly, having a significant influence on the global economy. Moreover, crude oil prices reached all-time highs. Combined with the preceding cluster results analysis, the data appeared in clusters in 2008, 2009, 2010, and 2011. This is because the financial downturn had a lingering effect on some countries after 2008, a significant period during which world tourists and financial markets suffered severe damage. Moreover, 2012 is an election year, and the Russian Federation, Hong Kong Special Administrative Region (China), Democratic People's Republic of Korea, United States of America, People's Republic of China, Japan, and South Korea have successively elected or de facto elected a new national leader. In 2013, an outbreak of the H7N9 influenza virus occurred. In addition, this year featured the general election in Malaysia. In 2015, Malaysia Development Berhad was implicated in a controversy. In addition, an extraordinary refugee crisis in Europe and an outbreak of the Zika virus between 2015 and 2016 occurred. The year 2017 marked the 60th anniversary of the Federation of Malaya's independence from Malaysia. Thus, different periods' responses to shocks for tourist arrivals were somewhat unpredictable. In general, by combining data cluster analysis and break analysis, the raw data used in the research has been impacted by a number of crises over a range of time periods. These crises include, among others, disease outbreaks, political security considerations, environmental disasters, and financial crises. After studying the characteristics of clusters exposed to a news shock, the analysis of both symmetric and asymmetric impact is simpler.

Table 3. Break points in Malaysia tourist arrivals time series.

Series	**Structural Break**				
Total Arrivals	2003M12	2007M01	2010M05	2013M12	2017M01
Singapore	2003M12	2007M03	2010M05	2013M12	2017M01
Indonesia	2003M11	2007M04	2010M04	2013M08	2016M10
China	2003M03	2005M07	2009M07	2012M07	2016M12
Thailand	2003M12	2006M12	2009M12	2012M12	2015M12
South Korea	2004M09	2007M11	2011M01	2014M01	2017M01
Japan	2003M01	2006M08	2009M08	2012M08	2016M02
Australia	2003M07	2006M07	2009M07	2012M08	2016M02
UK	2004M11	2007M12	2010M12	2013M12	2016M12
USA	2003M10	2006M11	2009M11	2012M12	2016M02
KLCI	2003M10	2006M11	2010M04	2013M04	2016M04
DXY	2003M01	2006M01	2009M01	2012M01	2015M01
S&P500	2005M01	2008M01	2011M01	2014M01	2017M01
CO	2003M01	2006M01	2009M01	2012M01	2015M01
GP	2004M09	2007M09	2010M09	2013M09	2017M01

6.3. Unit Root Test

This study applied the ADF and P.P. tests (intercept without trend and intercept with trend) to determine whether or not the log differences between monthly tourist arrivals in Malaysia and financial news shocks are considered stationary. The results and conclusions of the tests are summarized in Table 4. At a significance threshold of 1% between the two

datasets, the results of the two methodologies mentioned above were significantly greater than all critical values (asterisk shown). Therefore, it can be argued that the stationarity of the time series at the level of individual observations is guaranteed, and the data can be used for modelling.

Table 4. Unit Root Test.

Series	ADF		PP	
	Intercept without Trend	Intercept with Trend	Intercept without Trend	Intercept with Trend
Total Arrivals	−6.33 ***	−6.45 ***	−26.07 ***	−28.09 ***
Singapore	−5.93 ***	−6.17 ***	−33.46 ***	−45.24 ***
Indonesia	−5.15 ***	−5.19 ***	−47.58 ***	−65.12 ***
China	−10.23 ***	−10.22 ***	−28.00 ***	−28.12 ***
Thailand	−6.33 ***	−6.30 ***	−38.08 ***	−38.59 ***
South Korea	−3.92 ***	−3.91 ***	−35.24 ***	−35.02 ***
Japan	−5.64 ***	−5.66 ***	−35.29 ***	−35.30 ***
Australia	−5.77 ***	−5.80 ***	−32.31 ***	−32.23 ***
UK	−5.64 ***	−5.66 ***	−35.29 ***	−35.30 ***
USA	−5.81 ***	−5.81 ***	−29.07 ***	−29.12 ***
KLCI	−13.72 ***	−13.69 ***	−13.79 ***	−13.76 ***
DXY	−14.89 ***	−14.94 ***	−14.91 ***	−14.96 ***
S&P500	−14.68 ***	−14.85 ***	−14.75 ***	−14.89 ***
CO	−13.20 ***	−13.19 ***	−13.16 ***	−13.14 ***
GP	−17.42 ***	−17.44 ***	−17.50 ***	−17.58 ***

Notes: *** denotes significant at 1%.

6.4. Estimation and Diagnostic Tests of Methods for Modelling

It is crucial to first estimate the conditional mean equations and then applied the residual series produced from the conditional mean equations to estimate the conditional variances in the various volatility models. Standard practice is to assume that conditional mean equations are regression equations, including for all volatility models. Before conducting the modelling, analysis and evaluating the forecast of monthly tourist arrivals into Malaysia, the conditional mean equations were thoroughly documented in order to identify seasonality effects and series linkages. In contrast to the reference month (December), comparisons were performed between dummy variables from January to November, and the mean equations for all time series were displayed in a table. As shown in Table 5, the monthly seasonal dummy variables within the conditional mean equations are statistically significant at the 1%, 5%, and 10% levels, indicating that there were monthly seasonality effects for tourist arrivals and financial news shocks, respectively. Other studies undertaken in the past have discovered that the frequency of tourist arrivals in the nation varies from month to month and season to season (Coshall and Charlesworth 2011; Emili et al. 2020; Kim and Wong 2006; Kulendran and Wong 2005; Lim and McAleer 2001; Rosselló and Sansó 2017), as a result of which the findings demonstrate that they are compatible with the findings of this particular study.

The findings that are shown in Table 6 lend validity to the dynamics of volatility. As seen in the graph, the skewness and kurtosis statistics indicate that the value in a different series is skewed. While the results in the Jarque-Bera box are considered significant at the 1% and 5% levels, the results in the Ljung-Box box are deemed significant at the 1% and 5% levels, respectively. These results indicate that the residuals and residual squared figures are sequentially related. Examined models of volatility contain these figures, which illustrate the inherent characteristics of volatility in the context of monthly tourism demand in Malaysia when news shocks are considered.

Table 5. Mean Equation.

	Mean Equation												
Total Arrivals	$Y_t = 0.123$	$-0.114Y_{t-1}$	$-0.179January$	$-0.193February$	$-0.030March$	$-0.199April$	$-0.125May$	$-0.050June$	$-0.120July$	$-0.136August$	$-0.173September$	$-0.103October$	$-0.123November + \varepsilon_t$
	(5.664)	(−1.723)	(−5.543)	(−6.151)	(−0.971)	(−6.319)	(−4.000)	(−1.622)	(−3.866)	(−4.430)	(−5.622)	(−3.326)	(−3.990)
Singapore	$Y_t = 0.145$	$-0.277Y_{t-1}$	$-0.242January$	$-0.244February$	$-0.055March$	$-0.215April$	$-0.119May$	$-0.017June$	$-0.211July$	$-0.179August$	$-0.127September$	$-0.167October$	$-0.118November + \varepsilon_t$
	(5.074)	(−4.357)	(−5.865)	(−5.793)	(−1.353)	(−5.309)	(−2.896)	(−0.431)	(−5.219)	(−4.349)	(−3.139)	(−4.161)	(−2.915)
Indonesia	$Y_t = 0.167$	$-0.356Y_{t-1}$	$-0.178January$	$-0.361February$	$-0.140March$	$-0.185April$	$-0.150May$	$-0.029June$	$-0.015July$	$-0.343August$	$-0.241September$	$-0.046October$	$-0.185November + \varepsilon_t$
	(4.352)	(−5.715)	(−3.137)	(−6.622)	(−2.582)	(−3.388)	(−2.781)	(−0.531)	(−0.269)	(−6.248)	(−4.399)	(−0.845)	(−3.355)
China	$Y_t = 0.102$	$-0.212Y_{t-1}$	$-0.020January$	$+0.065February$	$-0.225March$	$-0.182April$	$-0.227May$	$-0.204June$	$+0.145July$	$+0.055August$	$-0.370September$	$-0.069October$	$-0.112November + \varepsilon_t$
	(1.985)	(−3.246)	(−0.275)	(0.888)	(−3.050)	(−2.488)	(−3.125)	(−2.804)	(2.001)	(0.735)	(−5.066)	(−0.930)	(−1.540)
Thailand	$Y_t = -0.018$	$-0.349Y_{t-1}$	$-0.044January$	$-0.005February$	$+0.157March$	$+0.157April$	$-0.053May$	$-0.046June$	$-0.027July$	$+0.029August$	$-0.058September$	$+0.175October$	$-0.028November + \varepsilon_t$
	(−0.493)	(−5.597)	(−0.876)	(−0.104)	(3.157)	(3.035)	(−1.038)	(−0.936)	(−0.534)	(0.591)	(−1.153)	(3.535)	(−0.534)
South Korea	$Y_t = 0.113$	$-0.398Y_{t-1}$	$+0.180January$	$-0.114February$	$-0.342March$	$-0.281April$	$-0.121May$	$-0.107June$	$+0.179July$	$+0.074August$	$-0.434September$	$-0.221October$	$+0.005November + \varepsilon_t$
	(2.476)	(−6.513)	(2.785)	(−1.748)	(−5.230)	(−4.248)	(−1.864)	(−1.667)	(2.782)	(1.139)	(−6.788)	(−3.173)	(0.077)
Japan	$Y_t = 0.016$	$-0.196Y_{t-1}$	$+0.031January$	$-0.012February$	$+0.118March$	$-0.320April$	$-0.077May$	$-0.046June$	$+0.137July$	$+0.217August$	$-0.044September$	$-0.112October$	$-0.085November + \varepsilon_t$
	(0.387)	(−3.007)	(0.544)	(−0.206)	(2.072)	(−5.508)	(−1.289)	(−0.803)	(2.410)	(3.720)	(−0.739)	(−1.975)	(−1.504)
Australia	$Y_t = 0.137$	$-0.346Y_{t-1}$	$+0.108January$	$-0.539February$	$-0.133March$	$-0.020April$	$-0.341May$	$-0.131June$	$+0.109July$	$-0.297August$	$-0.040September$	$-0.006October$	$-0.331November + \varepsilon_t$
	(3.327)	(−5.532)	(1.759)	(−8.897)	(−2.350)	(−0.339)	(−5.942)	(−2.399)	(1.879)	(−4.860)	(−0.734)	(−0.097)	(−5.743)
UK	$Y_t = 0.062$	$-0.409Y_{t-1}$	$+0.097January$	$-0.042February$	$+0.051March$	$-0.064April$	$-0.356May$	$-0.189June$	$+0.123July$	$+0.102August$	$-0.207September$	$-0.082October$	$-0.176November + \varepsilon_t$
	(1.107)	(−6.738)	(1.196)	(−0.523)	(0.643)	(−0.802)	(−4.527)	(−2.401)	(1.557)	(1.259)	(−2.603)	(−1.048)	(−2.218)
USA	$Y_t = 0.065$	$-0.137Y_{t-1}$	$+0.006January$	$-0.160February$	$+0.056March$	$-0.191April$	$-0.131May$	$+0.062June$	$+0.061July$	$-0.227August$	$-0.242September$	$+0.071October$	$-0.068November + \varepsilon_t$
	(1.895)	(−2.070)	(0.124)	(−3.239)	(1.150)	(−3.846)	(−2.668)	(1.273)	(1.239)	(−4.595)	(−4.875)	(1.441)	(−1.356)
KLCI	$Y_t = 0.017$	$+0.139Y_{t-1}$	$-0.009January$	$-0.014February$	$-0.017March$	$-0.015April$	$-0.025May$	$-0.017June$	$+0.000July$	$-0.028August$	$-0.033September$	$-0.002October$	$-0.023November + \varepsilon_t$
	(1.948)	(2.110)	(−0.692)	(−1.149)	(−1.367)	(−1.195)	(−2.006)	(−1.405)	(0.033)	(−2.245)	(−2.720)	(−0.148)	(−1.883)
DXY	$Y_t = -0.010$	$+0.052Y_{t-1}$	$+0.014January$	$+0.012February$	$+0.009March$	$+0.003April$	$+0.016May$	$+0.005June$	$+0.009July$	$+0.012August$	$+0.007September$	$+0.014October$	$+0.013November + \varepsilon_t$
	(−1.925)	(0.784)	(1.919)	(1.569)	(1.285)	(0.414)	(2.205)	(0.712)	(1.224)	(1.702)	(0.965)	(1.904)	(1.799)
S&P500	$Y_t = 0.000$	$+0.047Y_{t-1}$	$+0.004January$	$-0.001February$	$+0.011March$	$+0.016April$	$-0.001May$	$-0.007June$	$+0.008July$	$-0.003August$	$-0.010September$	$+0.010October$	$+0.011November + \varepsilon_t$
	(0.047)	(0.703)	(0.291)	(−0.101)	(0.803)	(1.142)	(−0.105)	(−0.511)	(0.550)	(−0.244)	(−0.741)	(0.740)	(0.791)
CO	$Y_t = -0.011$	$+0.129Y_{t-1}$	$+0.027January$	$+0.048February$	$+0.028March$	$+0.038April$	$+0.010May$	$+0.040June$	$-0.005July$	$+0.022August$	$-0.005September$	$-0.016October$	$-0.017November + \varepsilon_t$
	(−0.549)	(1.951)	(0.914)	(1.633)	(0.943)	(1.283)	(0.346)	(1.355)	(−0.168)	(0.743)	(−0.181)	(−0.538)	(−0.595)
GP	$Y_t = 0.005$	$-0.127Y_{t-1}$	$+0.026January$	$+0.015February$	$-0.013March$	$-0.004April$	$-0.003May$	$-0.004June$	$-0.005July$	$+0.016August$	$+0.009September$	$-0.011October$	$+0.008November + \varepsilon_t$
	(0.453)	(−1.917)	(1.711)	(0.971)	(−0.847)	(−0.235)	(−0.171)	(−0.276)	(−0.302)	(1.061)	(0.607)	(−0.696)	(0.548)

Table 6. Summary of statistics for ε_t.

	Median	Skewness	Kurtosis	Jarque-Bera
Total Arrivals	0.007597	−1.159040	9.772958	508.1939 ***
Singapore	0.005923	−0.775143	9.022760	383.5472 ***
Indonesia	0.000812	−0.549180	5.823914	91.04375 ***
China	0.014704	−0.913643	7.843233	265.7258 ***
Thailand	0.006159	−0.588754	6.577585	140.6743 ***
South Korea	0.002417	0.227203	5.187442	49.4979 ***
Japan	0.015244	−0.300143	6.993822	161.7504 ***
Australia	0.006117	−0.124243	5.088687	43.87487 ***
UK	0.002978	−0.543505	4.707822	40.64094 ***
USA	−0.011949	−2.432976	36.027870	11,052.3 ***
KLCI	0.002575	−0.436359	4.955315	45.46684 ***
DXY	0.000160	0.043616	3.558876	3.172851
S&P500	0.006242	−0.297695	3.606771	7.166383 **
CO	0.000764	−0.393150	3.942510	14.9404 ***
GP	0.007539	−0.855155	4.855112	63.13548 ***

Notes: *** denotes $p < 0.01$; ** denotes $p < 0.05$.

Tables 7–9 give the estimated parameters of the conditional variance equations and the estimated parameters of the conditional variance equations. These tables are derived from three distinct models of volatility that integrate a financial news shock. The parameter estimates were obtained using the BHHH (Berndt et al. 1974) numerical optimisation process by first maximising the log-likelihood function and then decreasing it. This procedure was repeated until precise parameter estimations were obtained. Despite this, the conditional variance equations for the three models alter depending on whether or not the dynamic process assumption of conditional variance has been considered. This is because the conditional variance equations alter when the dynamic process of conditional variance is included. When the prediction error is skewed, a conditional variance equation is used to express the conditional heteroscedasticity of the prediction error. In conjunction with financial news shocks impacts, conditional variance equations based on separate volatility models were employed to understand the forecast of Malaysian tourist arrivals. This study tries to determine if five financial news shocks have symmetric or asymmetric effects on Malaysian tourist arrivals. Using the results, we determined whether the GARCH family models are an adequate model for predicting the effect of a news shock on the volatility of Malaysian tourism demand based on the collected data.

An underlined value in the GARCH (1,1) models in Table 7 indicates the significance of financial news shocks (KLCI; DXY; S&P500; crude oil and gold price) at p values less than 10%, 5%, and 1%, respectively, in the model's parameters. Furthermore, it is also possible that these series have satisfied the steady-state conditions if $\alpha + \beta$ values are close to 1. Due to the proximity of $\alpha + \beta$ to 1, any news shocks are more likely to influence the demand for Malaysian tourism. Consequently, in the GARCH (1,1)-KLCI model, variations in KLCI impact the total tourist arrivals to Malaysia, Thailand, South Korea, Singapore, Indonesia, and the UK. Total arrivals and visitors from Indonesia, China, Australia, the UK, the USA, and South Korea are affected by DXY variation in the GARCH (1,1)-DXY model. However, in the GARCH (1,1)-S&P500 model, the S&P500 has no effect on total arrivals and visits from Thailand, Australia, and the UK. Based on the GARCH (1,1)-CO model, crude oil prices affect all tourists to Malaysia, excluding those from Indonesia. According to the GARCH (1,1)-GP model, the price of gold influences the total number of visitors to Malaysia, including those from Singapore, Indonesia, South Korea, the UK, and Australia. In the GARCH (1,1) model, five financial news shocks, followed by Australia, directly affect the number of British tourists to Malaysia. Therefore, when considered in conjunction with Figure 2, the irregular nature of visitor demand in response to major news events becomes conspicuous. On the other hand, the financial shocks have the most negligible impact on Japanese visitors to Malaysia. Moreover, several parameter estimations in all models of these ten series are judged not to be statistically significant at 10%, and this is true for all models, for example, as seen in the data from Japan in GARCH (1,1)-KLCI, Singapore in GARCH (1,1)-DXY, USA in GARCH (1,1)-S&P500, South Korea in GARCH (1,1)-CO, and China in GARCH (1,1)-GP. Accordingly, the findings of this research study stand in stark contrast to those of (Kim and Wong 2006).

Table 7. Conditional variance equation for GARCH model with financial news shocks.

Model		Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA
GARCH (1,1)-KLCI	ω_1	0.002 ***	0.005 ***	0.000 ***	0.000	0.000	0.000	0.001	0.019 ***	0.017 ***	0.000
	α_1	0.257 ***	0.178 ***	−0.050 ***	0.059 ***	−0.012 ***	0.064 **	0.085 **	−0.060 ***	0.062 **	0.109 **
	β_1	0.566 ***	0.463 ***	1.010 ***	0.921 ***	1.006 ***	0.917 ***	0.891 ***	0.464 ***	0.670 ***	0.868
	$KLCI_1$	**−0.037 *** **	**−0.096 *** **	**0.018*** **	−0.028	**0.023 *** **	**0.048 ** **	−0.030	−0.032	**0.213 *** **	0.014
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	194.026	139.812	86.224	30.992	88.081	46.146	81.419	6.034	3.073	108.188
GARCH (1,1)-DXY	ω_1	0.000	0.000 ***	0.008 ***	0.020 **	0.000	0.008 ***	0.000	0.000 ***	0.015 **	0.000
	α_1	−0.033 ***	−0.040 ***	0.037	0.206 ***	−0.023 ***	0.252 ***	0.095 **	−0.041 ***	0.056 **	0.168 ***
	β_1	1.024 ***	1.005 ***	0.584 ***	0.498 ***	1.015 ***	0.585 ***	0.890 ***	1.013 ***	0.687 ***	0.836 ***
	DXY_1	**0.015 ** **	0.010	**−0.186 *** **	**−0.442 *** **	−0.009	**−0.209 *** **	0.022	**0.046 * **	**−0.446 *** **	**0.046 * **
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	204.244	148.582	61.211	21.740	89.947	42.308	80.614	90.098	9.826	108.618
GARCH (1,1)-S&P500	ω_1	0.003 ***	0.000 ***	0.000 ***	0.000	0.000	0.000	0.000	0.000 ***	0.023 *	0.000
	α_1	0.080 ***	−0.057 ***	−0.043 ***	0.070 ***	−0.024 ***	0.028 *	0.091 **	−0.038 ***	0.073	0.105 ***
	β_1	0.551 ***	1.021 ***	1.004 ***	0.911 ***	1.013 ***	0.957 ***	0.892 ***	1.011 ***	0.565 ***	0.868 ***
	$S\&P500_1$	**−0.030 *** **	−0.001	0.004	−0.004	**0.009 * **	−0.001	−0.002	**−0.020 *** **	**0.123 *** **	0.006
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	187.114	152.522	84.592	30.595	90.645	45.217	80.438	91.764	4.992	108.333
GARCH (1,1)-CO	ω_1	0.002 ***	0.007 ***	0.001 ***	0.022 *	0.000	0.001 *	0.011 ***	0.000 ***	0.039 ***	0.001 *
	α_1	0.256 ***	0.185 ***	−0.052 ***	0.147 ***	−0.023 ***	0.106 *	0.165 ***	−0.044 ***	0.142	0.199 ***
	β_1	0.560 ***	0.381 ***	1.010 ***	0.560 ***	1.012 ***	0.855 ***	0.531 ***	1.014 ***	0.151	0.776 ***
	CO_1	**−0.028 *** **	**−0.085 *** **	−0.005	**0.221 *** **	**0.018 ** **	0.010	**0.109 *** **	**−0.010 * **	**0.263 *** **	**−0.026 * **
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	191.927	131.299	85.775	17.832	92.371	44.509	57.918	90.641	18.094	108.760
GARCH (1,1)-GP	ω_1	0.000 ***	0.000 ***	0.000 ***	0.001	0.000 ***	0.000	0.000	0.000 ***	0.025 *	0.000 *
	α_1	−0.019 ***	−0.031 ***	−0.046 ***	0.067 ***	−0.017 ***	0.036 ***	0.091 **	−0.015 ***	0.067 *	0.110 **
	β_1	1.006 ***	0.998 ***	1.009 ***	0.911 ***	0.995 ***	0.957 ***	0.891 ***	0.984 ***	0.543 ***	0.864 ***
	GP_1	**0.005 *** **	**0.010 *** **	**0.022 *** **	−0.012	−0.013	**0.037 ** **	−0.004	**0.017 ** **	**0.227 *** **	0.008
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	196.514	145.973	86.921	30.820	85.226	46.519	80.458	84.870	4.561	108.364

Notes: Adj. R^2: Adjusted R^2; LL: Log-likelihood; ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table 8. Conditional variance equation for EGARCH model with financial news shocks.

Model		Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA
EGARCH (1,1)-KLCI	ω_2	−0.016	−0.044	0.011	0.020	−0.017	0.063 ***	−4.559 ***	−0.026	−0.751 ***	0.050
	α_2	−0.114 *	−0.101 ***	−0.066	−0.067	−0.101 ***	−0.050 ***	−0.028	−0.080	0.356 ***	−0.097 **
	β_2	0.980 ***	0.974 ***	0.994 ***	0.992 ***	0.976 ***	1.011 ***	−0.351	0.979 ***	0.828 ***	0.996 ***
	ϕ	**−0.141** ***	**−0.093** ***	**−0.119** ***	−0.106	−0.015	**−0.146** ***	**−0.281** ***	**−0.119** ***	−0.031	**−0.185** **
	$KLCI_2$	**−1.946** ***	**−1.425** ***	**0.949** ***	**−2.216** ***	**−1.010** ***	−0.080	−0.250	−0.114	**10.816** ***	**−1.499** **
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	211.727	153.820	88.613	42.181	90.919	53.317	51.960	88.936	10.627	113.895
EGARCH (1,1)-DXY	ω_2	0.058	−0.019	0.025 ***	−0.100 **	0.000	0.065 ***	−0.185 **	−0.020	−0.656 ***	0.063 ***
	α_2	−0.104 **	−0.082 **	−0.138 ***	0.045	−0.075 *	−0.047 ***	0.163 ***	−0.089 *	0.242 ***	−0.084 ***
	β_2	0.997 ***	0.983 ***	0.984 ***	0.985 ***	0.986 ***	1.012 ***	0.988 ***	0.979 ***	0.840 ***	1.005 ***
	ϕ	**−0.166** ***	**−0.109** ***	**−0.116** ***	**−0.175** ***	0.027	**−0.144** ***	**−0.095** *	**−0.119** ***	**−0.132** **	**−0.287** ***
	DXY_2	1.831	0.169	**−3.020** **	−1.293	**1.824** *	1.122	−0.301	−0.587	**−18.068** ***	**2.993** ***
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	209.983	152.198	91.528	34.322	90.381	53.693	80.213	89.392	18.790	112.652
EGARCH (1,1)-S&P500	ω_2	0.032	−0.004	0.000	0.037	−4.478 ***	0.061 ***	−6.524 ***	−0.010	−0.730 ***	−0.191 *
	α_2	−0.095 *	−0.104 ***	−0.080 *	−0.045	0.016	−0.046 ***	0.066	−0.079	0.229 ***	0.124 *
	β_2	0.993 ***	0.982 ***	0.988 ***	1.003 ***	−0.224 **	1.011 ***	−0.885 ***	0.983 ***	0.805 ***	0.982 ***
	ϕ	**−0.137** ***	**−0.091** ***	**−0.122** ***	**−0.134** ***	−0.240	**−0.132** ***	**−0.181** ***	**−0.065** *	−0.056	**−0.219** ***
	$S\&P500_2$	**−0.895** ***	−0.237	0.516	**−1.122** ***	0.915	−0.345	**0.727** *	**−0.768** *	**4.772** ***	0.484
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	209.867	154.027	88.345	39.221	76.176	53.660	55.473	90.670	13.968	110.546
ERGARCH (1,1)-CO	ω_2	0.000	−0.010 ***	0.000	0.035	−4.134 ***	0.062	−6.516 ***	−0.018	−1.439 ***	0.035
	α_2	−0.071 ***	−0.081 ***	−0.079 *	−0.047	0.081	−0.055	0.069	−0.087 *	0.546 ***	−0.071 *
	β_2	0.990 ***	0.986 ***	0.989 ***	1.002 ***	−0.108	1.009 ***	−0.879 ***	0.979 ***	0.683 ***	0.998 ***
	ϕ	**−0.164** ***	**−0.165** ***	**−0.130** ***	**−0.132** ***	**−0.263** ***	**−0.136** ***	**−0.196** ***	**−0.122** ***	**−0.261** **	**−0.224** ***
	CO_2	**−0.610** *	0.395	0.510	**−1.057** **	**4.559** **	**−0.847** *	**2.353** *	0.199	**13.711** ***	**−1.071** *
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	205.934	152.291	87.962	37.588	78.389	54.855	56.281	89.387	41.411	112.730
EGARCH (1,1)-GP	ω_2	−0.012	−0.039 *	0.015 ***	0.016	−0.034 ***	0.059	−6.646 ***	−0.028	−3.642 ***	−0.146 *
	α_2	−0.079 ***	−0.096 ***	−0.083 ***	−0.081 *	−0.049 ***	−0.034	0.070	−0.101 **	0.474 ***	0.094
	β_2	0.988 ***	0.977 ***	0.991 ***	0.991 ***	−0.072 ***	1.015 ***	−0.913 ***	0.974 ***	0.236	0.987 ***
	ϕ	**−0.184** ***	**−0.116** ***	**−0.097** *	**−0.195** ***	**0.984** ***	**−0.181** ***	**−0.155** ***	**−0.130** ***	**−0.143** ***	**−0.227** **
	GP_2	**−1.231** ***	**−1.409** ***	**0.670** *	**−2.135** ***	**−1.095** ***	**1.002** *	−0.902	**−1.012****	**12.450** ***	**0.237**
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	206.867	154.037	88.371	41.627	85.712	54.344	55.053	90.325	8.750	110.320

Notes: Adj. R^2: Adjusted R^2; LL: Log-likelihood; ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table 9. Conditional variance equation for GJRGARCH model with financial news shocks.

Model		Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA
GJRGARCH (1,1)-KLCI	ω_3	0.001 ***	0.008 ***	0.000 ***	0.001	0.000 ***	0.000 **	0.000 *	0.000 ***	0.024 **	0.000
	α_3	−0.021	0.079	−0.071 ***	0.011	−0.061 ***	−0.073 ***	−0.039	−0.081 ***	0.020	−0.111 **
	β_3	0.803 ***	0.451 ***	1.010 ***	0.924 ***	0.062 ***	1.013 ***	0.930 ***	0.085 ***	0.556 ***	0.926 ***
	λ	**0.225** ***	0.076	0.036	0.077	**1.027** ***	**0.128** ***	**0.156** ***	**1.004** ***	0.082	**0.293** ***
	$KLCI_3$	**−0.025** ***	**−0.132** ***	0.012	−0.029	−0.008	0.027 **	−0.027	0.002	**0.247** ***	0.012
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	1.969	136.197	86.956	31.601	92.235	53.816	83.878	90.482	3.088	111.863
GJRGARCH (1,1)-DXY	ω_3	0.002 ***	0.000 ***	0.000 ***	0.009 ***	0.000	0.007 ***	0.000	0.000 ***	0.029 ***	0.000
	α_3	0.070	−0.095 ***	−0.072 ***	0.123 *	−0.022 ***	0.103	−0.040	−0.088 ***	0.045	−0.113 **
	β_3	0.540 ***	1.012 ***	1.001 ***	0.581 *	1.015	0.614 ***	0.925 **	1.013 ***	0.418 **	0.946 ***
	λ	0.363 ***	0.089 **	0.060 ***	0.243 ***	0.000	0.306 *	0.179 **	0.080 *	0.090	0.268 ***
	DXY_3	0.077 ***	0.002	−0.008	−0.269 ***	−0.006	−0.206 ***	0.051 ***	0.019	−0.567 ***	0.036
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	194.073	155.197	85.093	29.089	89.831	43.752	83.548	92.353	9.205	111.684
GJRGARCH (1,1)-S&P500	ω_3	0.000 ***	0.000 ***	0.001 ***	0.001	0.000	0.000 **	0.000	0.000 ***	0.023 *	0.000 *
	α_3	−0.056 ***	−0.091 ***	−0.075 ***	0.024	−0.040 ***	−0.059 ***	−0.036	−0.076 ***	0.015	−0.109 *
	β_3	1.023 ***	1.012 ***	1.009 ***	0.909 ***	1.013 ***	1.013 ***	0.926 ***	1.011 ***	0.569 ***	0.919 ***
	λ	0.038	**0.080** *	**0.042** *	0.081	**0.032** **	**0.098** ***	**0.159** ***	**0.065** *	0.094	**0.296** ***
	$S\&P500_3$	**−0.003** *	0.000	0.002	−0.005	**0.010** **	−0.006	−0.002	**−0.013** *	**0.123** ***	0.006
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	205.193	154.981	86.650	31.154	91.442	52.774	82.735	93.242	5.585	112.189
GJRGARCH (1,1)-CO	ω_3	0.001 ***	0.007 ***	0.001 ***	0.016 ***	0.000	0.003 ***	0.013 *	0.000 ***	0.008 **	0.000 ***
	α_3	0.085	0.052	−0.075 ***	0.075	−0.036 ***	0.072	−0.024	−0.087 ***	0.262	−0.184 ***
	β_3	0.645 ***	0.411 ***	1.010 ***	0.460 ***	0.026 ***	0.681 ***	0.497 *	1.014 ***	0.530 ***	1.002 ***
	λ	**0.224** ***	**0.196** *	**0.043** *	**0.383** ***	**1.012** *	**0.228** ***	**0.293** *	**0.075** *	0.305	**0.297** ***
	CO_3	**−0.026** ***	**−0.087** ***	−0.004	**0.139** ***	**0.019** **	**0.053** ***	**0.114** *	−0.004	**0.121** ***	**−0.013** ***
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	193.911	132.122	86.778	28.481	92.978	41.485	60.881	91.250	59.059	113.936
GJRGARCH (1,1)-GP	ω_3	0.000 **	0.000 ***	0.000 ***	0.001 *	0.001 ***	0.000 **	0.000	0.000 ***	0.027 **	0.004 ***
	α_3	−0.019	−0.128 ***	−0.063 ***	0.001	−0.117 ***	−0.064 ***	−0.034	−0.089 ***	0.020	0.460 ***
	β_3	0.908 ***	0.194 ***	1.011 ***	0.919 ***	0.148 ***	1.014 ***	0.923 ***	1.013 ***	0.510	0.490 ***
	λ	**0.125** ***	**0.973** ***	0.023	**0.097** *	**0.963** ***	**0.111** ***	**0.160** ***	**0.079** *	**0.077** **	**−0.183** ***
	GP_3	0.000	0.004	**0.016** *	−0.018	**−0.102** ***	**0.022** *	−0.004	0.002	**0.234** ***	**0.050** ***
	Adj. R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	LL	194.477	147.928	87.389	31.677	87.090	53.781	82.767	92.189	4.882	104.980

Notes: Adj. R^2: Adjusted R^2; LL: Log-likelihood; ***, **, and * denote significant at 1%, 5% and 10%, respectively.

In contrast, the GARCH (1,1) model with financial news shocks is incapable of examining asymmetric effects and the influence of a positive or negative news shock on leverage (French et al. 1987; Nelson 1990; Schwert 1990). There is evidence of an asymmetric effect, indicating that the news has a differential impact on the volatility of tourism demand. According to the leverage effect, negative news is more likely than positive news to generate expected volatility in visitor demand. Because it assumes that the effects of positive and negative shocks are identical, or "symmetric" the model in Equation (1) may be problematic when applied to data regarding tourism demand. This is typical because the conditional variance is based on the amount of the delayed residual rather than its sign. Still, there is a possibility that a negative tourist shock could raise volatility more than a positive tourism shock of the same magnitude. Due to this issue, GJRGARCH and EGARCH models were developed, alongside other "asymmetric" volatility models.

The GARCH model predicts that the number of visitors visiting Malaysia will fluctuate because they are frequently affected by news shocks. However, it should be emphasised that our ability to determine the asymmetry and leverage effects, in this case, is limited. In contrast to the GARCH model, however, the EGARCH model offers two key advantages. First, it is expected that, because of the logarithmic structure of the EGARCH, the estimated conditional variance will not be negative in all instances. Therefore, the nonnegativity requirements used in estimating GARCH models are no longer necessary for assessing the EGARCH model. The following hypotheses can be used to test for the existence of asymmetry and leverage effects: $\phi \neq 0$ and $\phi < 0$.

Asymmetric effects occur when ϕ is not equal to zero, symmetric effects occur when ϕ is equal to zero, and leverage effects occur when ϕ is less than zero. Therefore, unlike GARCH models, the EGARCH model's news impact curve may have different positive and negative slopes, with the centre being located at $\varepsilon_{t-1}^2 = 0$. In the EGARCH (1,1) models in Table 8 that include the financial news shocks, all of the coefficients ϕ denoted by the highlighted symbol indicate that they are significant at 1%, 5%, and 10%, respectively. These values show that ϕ is less than zero, indicating that leverage effects occur in the models. In addition, the fact that has a negative sign of ϕ implies that the influence of a negative news shock on Malaysia's monthly tourism demand shifts by a substantially more significant amount than the impact of a good news shock does. The EGARCH (1,1)-KLCI model and the EGARCH (1,1)-S&P500 model find no evidence of leverage or asymmetry effects in the data for Thailand and the UK, respectively. Only Thailand lacks leverage and asymmetric effects in the EGARCH (1,1)-DXY. The other countries all have them. The leverage effects of EGARCH (1,1)-CO and EGARCH (1,1)-GP exist in the tourists from all countries entering Malaysia, except for the coefficient ($\phi > 0$) in the GARCH (1,1)-GP of Thailand, which has asymmetric effects. Overall, the DXY, Crude oil price, and gold price cause inbound tourist arrivals in Malaysia to exhibit higher leverage or asymmetric impacts. The "News Impact Curve" section can display these more clearly.

Financial news shocks have an effect on the overall number of arrivals and the number of British tourists that travel to Malaysia. These effects are dependent on the asymmetry and leverage effects outlined previously. According to the EGARCH (1,1) model, the KLCI has an impact on tourists from Singapore, Indonesia, China, Thailand, the UK, and the USA; the DXY has an impact on tourists from Indonesia, Thailand, the UK, and the USA; the S&P500 has an impact on tourist arrivals from China, Japan, Australia, and the UK; and crude oil has an impact on tourists from China, Thailand, South Korea, Japan, and the UK.

The asymmetric GJRGARCH model makes it possible for the conditional variance to respond differently to bad and good news while the leverage effect is being evaluated. This is achievable due to the fact that the model allows for the examination of the conditional variance. Depending on $\gamma > 0$ and $\gamma \neq 0$, the sign of γ in the GJRGARCH models may indicate that the asymmetry and leverage effects are significant at the 1%, 5%, and 10% levels, respectively. On the basis of these data, it can be concluded that negative financial news shocks are a crucial factor that considerably affects and influences the monthly volatility of tourist demand in the GJRGARCH (1,1) model presented in Table 9. In the

GJRGARCH (1,1)-KLCI model, the GJRGARCH (1,1)-DXY model, the GJRGARCH (1,1)-S&P500 model, the GJRGARCH (1,1)-CO model, and the GJRGARCH (1,1)-GP model, for instance, there are both leverage and asymmetry impacts in South Korea, Japan, Australia, and the USA, respectively. Meanwhile, there are leverage or asymmetric impacts on all other nations in the GJRGARCH (1,1)-CO model and the GJRGARCH (1,1)-GP model, correspondingly, with the exception of the UK and Indonesia. The GJRGARCH (1,1)-KLCI is the indicator that has the least amount of leverage or asymmetrical impacts on all nations. The news impact curve allows one to examine all of these things and more.

According to the findings of the study of asymmetry and leverage effects in the GJRGARCH (1,1) in conjunction with the impact of financial news, the KLCI influenced the total number of visitors to Singapore and the UK; the DXY index influences the number of tourists arriving from China, South Korea, Japan, and the UK. The S&P500 index influences the number of visitors from Thailand, Australia, and the UK. Changes in the number of tourists arriving from countries other than Australia are influenced by crude oil. The GP index influences the number of visitors from Indonesia, Thailand, South Korea, the UK, and the USA, and any shocking financial news will affect the number of British tourists visiting Malaysia.

The values for adjusted R^2 and log-likelihood are included in the tables that are displayed above them. These are used to analyse and investigate the conditional variance, which is determined based on the prediction ability of each volatility model. The adjusted R^2 values for the EGARCH (1,1) model are the highest, and the model's log-likelihood performance is superior to that of both GJRGARCH (1,1) and GARCH (1,1). As a result, this suggests that the EGARCH model, which was used in this research investigation, possessed the most astonishing and important capacity to forecast and predict conditional variance. Overall, the parameter of ϕ and γ in EGARCH and GJRGARCH is significant in these ten series at values of 1%, 5%, and 10%, respectively. These findings give evidence of the asymmetric and leveraging implications from the factor of news shocks in the various nations on the EGARCH (1,1) with financial news shocks model and the GJRGARCH (1,1) with financial news shocks model, respectively. These models were used for data analysis. The news impact curve will be used to compare the GARCH (1,1), EGARCH (1,1), and GJRGARCH (1,1) models. This distinction is crucially important. The tourist arrivals from the UK and the total tourist arrivals in Malaysia are the sequences most affected by financial news shocks, which applies to all three models. Thailand follows Vietnam closely in second place and South Korea in third. Australia's visitors to Malaysia are least likely to be affected by the recent financial news.

6.5. Estimation of News Impact Curve

To give additional evidence for the existence of asymmetry and leverage, we track the effects of shocks on conditional volatility and depict the news impact curves (NIC) using parameter estimates from all models. This helps demonstrate the existence of leverage and asymmetry. (Engle and Ng 1993) established a news impact curve to quantify the incorporation of news shocks into the estimate of volatility models. The estimated news impact curves are illustrated in Figure 6. Plots of the current conditional volatility (σ^2) vs. the past innovation (ε_{t-1}) are depicted in these graphs. A number of tools may be used to compare and contrast various alternative models in terms of their ability to represent the asymmetric impact or the leverage effects. Meanwhile, the GARCH model's asymmetry dictates that the conditional volatility should be affected differently by previous positive and negative shocks of the same size, namely NIC ($|\epsilon t-1|$) $\neq$ NIC ($-|\epsilon t-1|$). As previously established, the leverage effect holds when volatility is reduced by a positive shock, while a negative shock increases volatility. GARCH (1,1) with news shocks has a symmetric and U-shaped curve, indicating that previous positive and negative shocks of equal magnitude have the same influence on conditional volatility, according to this study's results. The leverage effect is valid when volatility is decreased by a positive shock, as it was previously established, and it is valid when volatility is raised by a negative shock, as

it was previously established. According to the findings of this research, the GARCH (1,1) model with news shocks has a symmetric and U-shaped curve. This indicates that prior shocks of comparable magnitude, whether they were positive or negative, had the same impact on conditional volatility. The EGARCH and GJRGARCH models, on the other hand, suggest that the consequences of positive or negative shocks are asymmetric for positive news ($\varepsilon_{t-1} > 0$) and negative news ($\varepsilon_{t-1} < 0$).

As can be seen in Figure 6, the GARCH model produces a news impact curve that is symmetric and centred at the value, $\varepsilon_{t-1} = 0$. The EGARCH and GJRGARCH news impact curves were asymmetric, with steeper slopes when $\varepsilon_{t-1} > 0$ than when $\varepsilon_{t-1} < 0$. The findings were in line with what was predicted for the signs of and in the conditional variance equations shown in Tables 8 and 9. This research shows that negative shocks are more likely to generate volatility than positive shocks of comparable magnitude. Consequently, the asymmetry and leverage effects are incorporated into models of the volatility of Malaysia's monthly inbound tourist demand.

The conditional variances on ε_{t-1} in the EGARCH model were practically comparably low when compared to the other two news impact curves (EGARCH and GJRGARCH), which were found in five financial news shocks among ten series. This suggests that volatility models for Malaysian monthly inbound tourist demand took the asymmetry and leverage effects into account. In particular, with this exception, the EGARCH model has also demonstrated the capacity to anticipate Malaysian tourist arrivals. For instance, this model has high prediction power for all five financial news shocks in both Australia and Indonesia. The GJRGARCH model, on the other hand, has quite substantial conditional variances on ε_{t-1}. Because it was able to predict the volatility of monthly visitor arrivals in Malaysia despite the news shocks, the GJRGARCH model must have been correct in its predictions. The GARCH model showed the same variance in the absolute value of ε_{t-1} as it did on any other value, due to the curve's symmetric structure. This shows that larger shocks can forecast higher levels of volatility at a rate proportional to the square of their magnitude. This increase in volatility is proportional to the square of the magnitude of the shocks. As a result, the volatility of monthly tourist arrivals in Malaysia may be overpredicted in response to positive news, whilst the volatility of monthly tourist demand in Malaysia may be underpredicted in response to negative news. This is because good news may lead to an overestimation of the monthly volatility of the number of tourists entering Malaysia.

6.6. In-Sample Prediction Performance

The results of the in-sample forecasting undertaken for this study are presented in Tables 10 and 11. These tables include all strategies for estimating the volatility of tourism demand for five news shocks in ten distinct series. We determined that GJRGARCH would serve as our benchmark model for computing and calculating Theil-U values using MAE and RMSE. This is due to the fact that, on average, the GJRGARCH model tends to give more accurate estimates than other GARCH models (Taylor 2004). Using the mean Theil-U value as a standard, a relative comparison was made between each of the distinct series. Therefore, the Theil-U measurement was computed and established for each series using the ratios created by the GJRGARCH method. The lower this indicator's value, the better the performance of the forecasting model is judged to be. In the final column of these tables, the outcomes of all forecasting methods are presented, with a focus on the ways that have proven to be the most accurate relative to those that have been considerably less accurate. Exemplary models are denoted by bold, underlined lines.

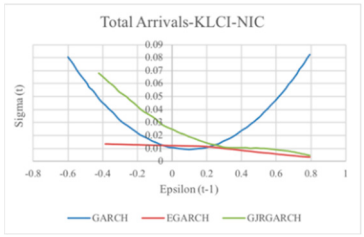
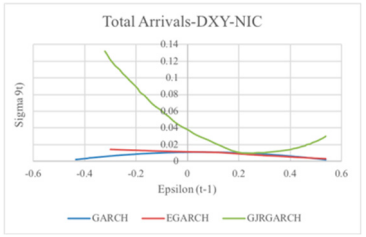
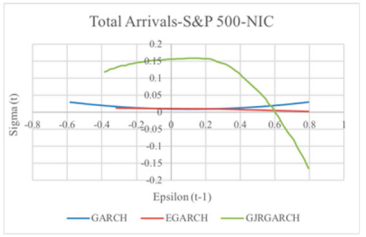
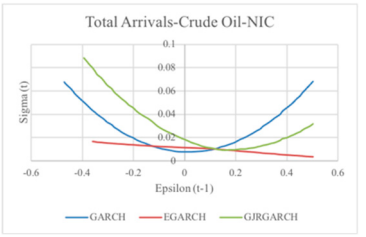
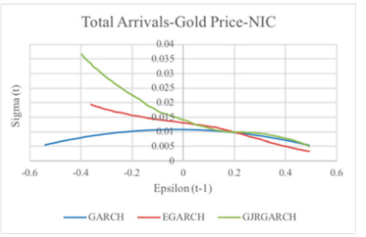
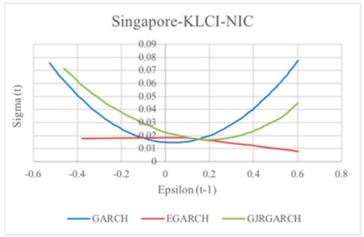
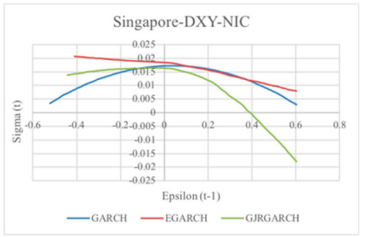
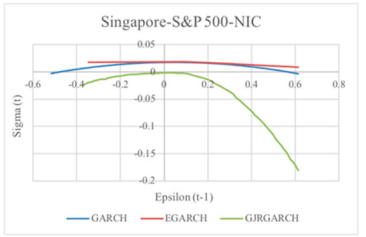
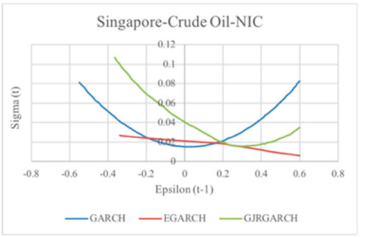
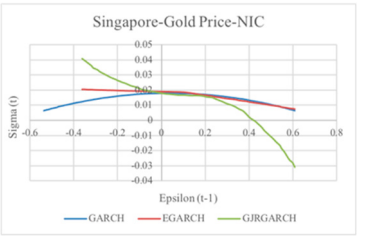
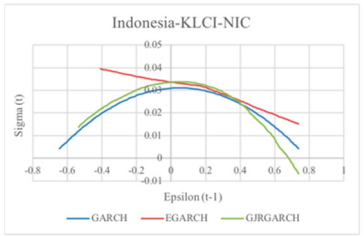
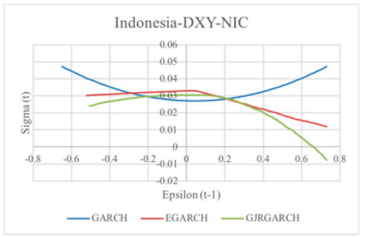
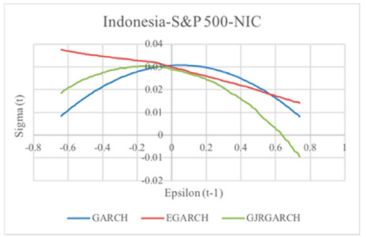
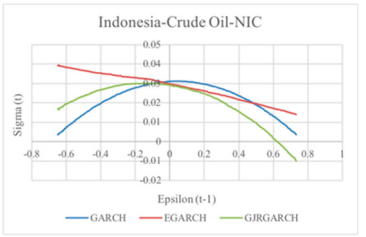
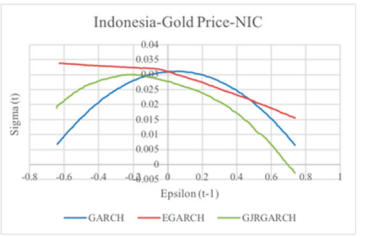
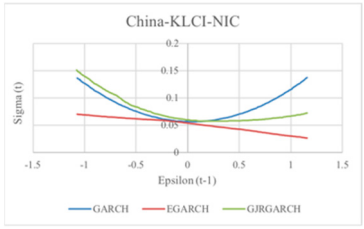
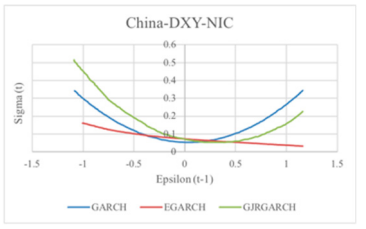
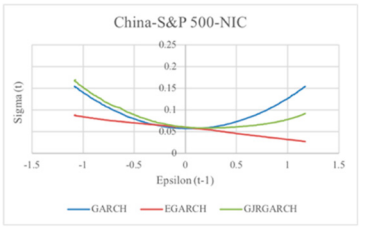
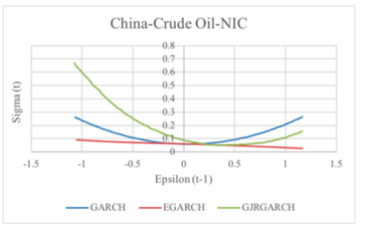
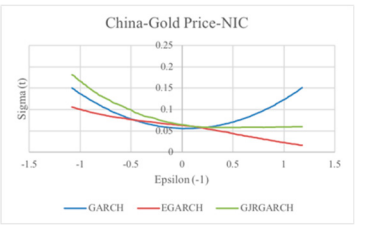
	KLCI	DXY	S&P500	Crude Oil	Gold Price
Total Arrivals					
Singapore					
Indonesia					
China					

Figure 6. *Cont.*

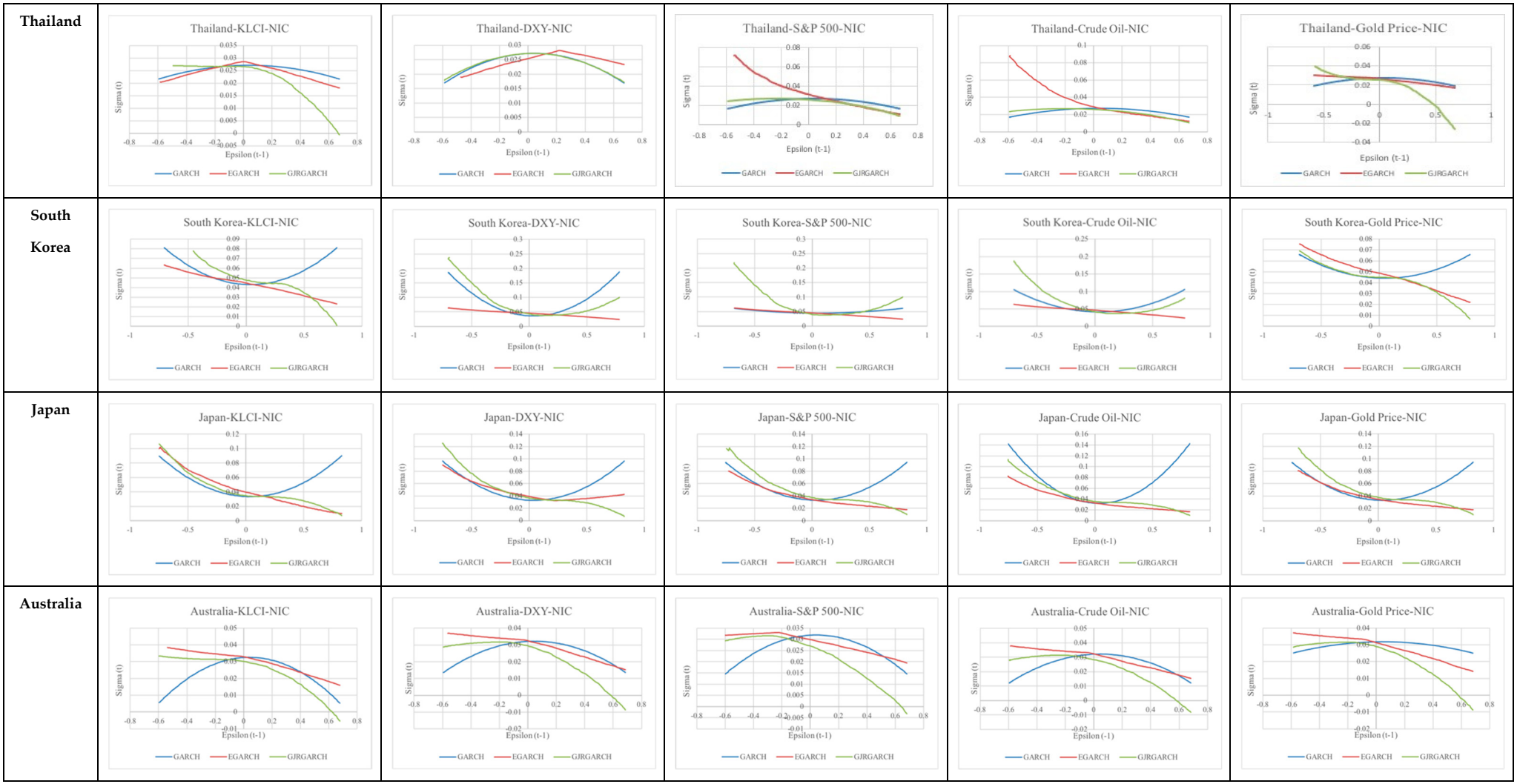


Figure 6. *Cont.*

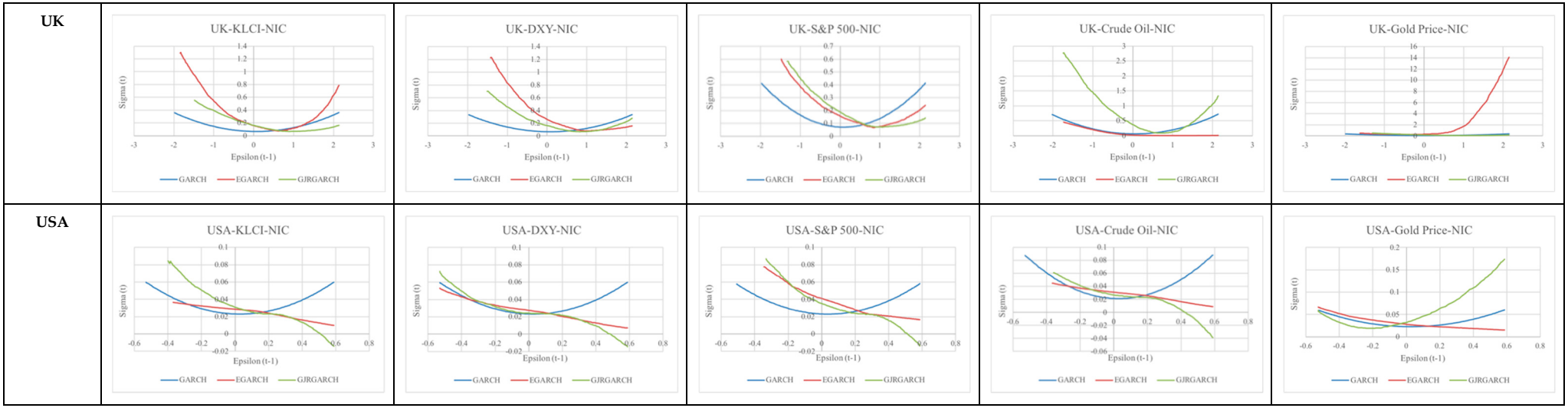


Figure 6. The 50 news impact curves in three volatility models with five financial news shocks.

Table 10. Tourism demand volatility prediction methods based on MAE for in-sample one-step-ahead predictions.

News Shocks	Model	Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA	Mean Theil-U	Rank
KLCI	GARCH (1,1)	0.997	0.888	0.982	1.014	1.024	1.042	1.018	1.159	0.970	1.045	1.014	7
	EGARCH(1,1)	1.143	0.982	0.848	1.036	1.119	1.002	1.236	0.933	1.055	1.076	1.043	14
	GJRGARCH(1,1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**	**3**
DXY	GARCH(1,1)	1.119	1.020	0.818	1.076	1.126	0.986	1.022	0.976	0.946	1.052	1.014	8
	EGARCH(1,1)	1.072	0.909	0.847	0.976	1.106	1.007	1.000	0.916	1.023	1.074	**0.993**	**1**
	GJRGARCH(1,1)	1.092	0.943	1.018	0.919	1.130	0.973	1.004	0.997	0.975	1.012	**1.006**	**4**
S&P500	GARCH(1,1)	1.141	1.029	0.998	1.009	1.114	1.063	1.019	0.971	0.964	1.049	1.036	13
	EGARCH(1,1)	1.057	0.921	0.880	0.971	1.188	1.021	1.263	0.954	0.995	0.998	1.025	11
	GJRGARCH(1,1)	1.075	0.949	1.013	0.989	1.013	1.016	0.993	0.991	0.985	1.076	1.010	6
CO	GARCH(1,1)	1.009	0.946	1.006	1.177	1.279	1.010	1.110	0.961	0.972	1.012	1.048	15
	EGARCH(1,1)	1.030	0.890	0.889	0.984	1.204	1.012	1.271	0.923	1.081	1.012	1.030	12
	GJRGARCH(1,1)	1.021	0.951	1.018	1.008	1.148	0.933	1.087	0.996	0.828	0.959	**0.995**	**2**
GP	GARCH(1,1)	1.103	1.004	0.979	1.008	1.081	1.074	1.020	0.924	0.979	1.043	1.021	10
	EGARCH(1,1)	1.036	0.928	0.909	0.975	1.061	0.991	1.256	0.952	1.084	0.998	1.019	9
	GJRGARCH(1,1)	1.035	0.852	0.994	0.991	1.153	1.012	0.994	0.988	1.003	1.056	**1.008**	**5**

Table 11. Tourism demand volatility prediction methods based on RMSE for in-sample one-step-ahead predictions.

News Shocks	Model	Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA	Mean Theil-U	Rank
KLCI	GARCH (1,1)	1.012	0.967	0.996	1.024	1.019	0.947	0.996	1.110	0.993	1.034	**1.010**	**5**
	EGARCH(1,1)	1.142	1.021	0.914	1.074	1.110	0.981	1.115	0.984	0.971	1.046	1.036	14
	GJRGARCH(1,1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**	**3**
DXY	GARCH(1,1)	1.180	1.038	0.970	0.958	1.113	0.881	0.989	1.005	1.001	1.001	1.014	6
	EGARCH(1,1)	1.121	1.002	0.922	0.994	1.108	0.979	0.991	0.983	1.029	1.034	1.016	7
	GJRGARCH(1,1)	0.995	1.008	0.999	0.856	1.112	0.889	0.992	1.008	1.000	0.996	**0.985**	**2**
S&P500	GARCH(1,1)	1.147	1.044	0.999	1.010	1.117	0.981	0.991	0.997	0.992	1.037	1.032	11
	EGARCH(1,1)	1.122	1.005	0.923	1.049	1.151	0.979	1.129	0.991	1.015	0.972	1.034	13
	GJRGARCH(1,1)	1.170	1.011	1.007	0.980	1.008	0.995	0.996	1.002	0.997	1.072	1.024	9
CO	GARCH(1,1)	1.006	0.979	1.009	0.994	1.180	0.916	1.019	0.999	1.007	0.984	**1.009**	**4**
	EGARCH(1,1)	1.128	0.987	0.928	1.061	1.157	0.974	1.133	0.985	1.089	1.024	1.046	15
	GJRGARCH(1,1)	0.973	0.983	1.011	0.904	1.088	0.910	1.035	1.004	0.860	0.953	**0.972**	**1**
GP	GARCH(1,1)	1.182	1.033	0.994	1.014	1.114	0.974	0.991	0.995	1.000	1.033	1.033	12
	EGARCH(1,1)	1.123	1.000	0.935	1.041	1.095	0.974	1.128	0.988	1.053	0.976	1.031	10
	GJRGARCH(1,1)	1.060	0.980	0.999	0.990	1.125	0.997	0.995	1.003	1.009	1.050	1.021	8

The mean Theil-U of GJRGARCH has the lowest value when compared to other models utilising MAE as the evaluation metric. This indicates that the GJRGARCH in KLCI, DXY, crude oil, and gold price is in the first place, followed by the EGARCH in DXY. Significantly, the DXY model with the highest ranking has the biggest impact on Malaysian tourists visiting MAE. Using the root-mean-squared error (RMSE) as the assessment metric, the GJRGARCH technique is the most accurate predictive method, followed by the GARCH methodology. Comparing these several techniques holistically, we discovered that the GJRGARCH modelling performs the best, followed by the EGARCH or GARCH models in the context of forecasting the volatility of the in-sample Malaysian tourism demand. In addition to KLCI and crude oil, the top models impact visitor arrivals most. This was identified by comparing the GJRGARCH model to the EGARCH and GARCH models. This conclusion is consistent with the previously presented news impact curve data. When applied to the S&P500 and crude oil in MAE and when applied to the S&P500 and gold price in RMSE, we notice that all three techniques exhibit predictive capacities. This suggests that these alarming news items have a diminished effect on the number of tourists visiting Malaysia.

6.7. Post-Sample Forecasting Performance

However, as a limitation and a caution, it should always be kept in mind that significantly "better" in-sample diagnostic tests and goodness-of-fit evaluations do not always indicate improved prediction accuracy, which should be considered. A greater prediction technique, for instance, would be able to withstand the use of data from outside the sample set. Combining the results of the in-sample and out-of-sample forecasts, Tables 12 and 13, respectively, are presented in this study. Additionally, bold and underlined lines denote models with a high rank. Regarding the MAE, the GJRGARCH model is far superior to the GARCH and EGARCH models. Nevertheless, compared to the in-sample, the performance of the GARCH model in MAE is superior to that of EGARCH. The S&P500 and gold price models with the highest rank (GJRGARCH (1,1) and GARCH (1,1)) had the largest influence on tourist arrivals. Similarly, the GJRGARCH model is regarded as the most effective method for predicting based on the RMSE. The three methods applied by DXY under MAE and RMSE result in the inaccuracy of performance projections. As a result, the DXY has a diminished effect on the number of tourists who visit Malaysia. Overall, despite the fact that the GARCH model can only perform symmetric analysis in the news impact curve, it performs well in predicting tourists in terms of MAE and RMSE for out-of-sample data. In contrast to MAE and RMSE, S&P500 and gold price had a bigger impact on inbound tourists.

Table 12. Tourism demand volatility forecasting methods based on MAE for out-of-sample one-step-ahead forecasting.

News Shocks	Model	Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA	Mean Thiel-U	Rank
KLCI	GARCH (1,1)	0.961	0.734	1.000	0.930	0.948	1.035	0.941	1.674	0.929	0.924	1.008	6
	EGARCH(1,1)	2.910	1.570	1.003	1.568	2.802	1.041	2.288	1.474	0.464	1.120	1.624	15
	GJRGARCH(1,1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**	**5**
DXY	GARCH(1,1)	1.245	0.750	1.446	2.464	0.636	1.704	0.869	0.950	0.878	0.930	1.187	10
	EGARCH(1,1)	2.974	1.180	1.001	0.818	2.548	1.034	0.898	1.389	0.560	1.472	1.387	11
	GJRGARCH(1,1)	1.057	0.623	1.062	1.463	0.641	1.691	0.945	1.003	0.939	1.015	1.044	7
S&P500	GARCH(1,1)	1.267	0.634	1.041	0.833	0.612	1.118	0.867	1.153	0.982	0.951	**0.946**	**1**
	EGARCH(1,1)	3.311	1.600	0.993	1.497	2.072	1.026	2.420	1.564	0.720	0.963	1.617	14
	GJRGARCH(1,1)	1.181	0.605	1.018	0.897	0.989	1.020	0.923	1.158	1.001	1.163	**0.996**	**3**
CO	GARCH(1,1)	0.985	0.833	1.166	3.015	2.489	1.254	1.712	0.986	0.843	0.954	1.424	12
	EGARCH(1,1)	2.383	1.164	1.002	1.166	1.970	1.079	2.682	1.376	0.529	1.958	1.531	13
	GJRGARCH(1,1)	0.997	0.874	1.104	1.816	1.822	1.194	1.730	1.011	0.371	0.807	1.173	9
GP	GARCH(1,1)	0.840	0.671	1.223	0.836	0.981	1.108	0.863	0.982	1.051	0.964	**0.952**	**2**
	EGARCH(1,1)	1.222	0.858	1.110	0.733	0.856	1.010	2.400	1.315	1.001	1.009	1.151	8
	GJRGARCH(1,1)	0.803	0.586	1.114	0.905	1.401	1.099	0.913	0.979	1.079	1.087	**0.996**	**4**

Table 13. Tourism demand volatility forecasting methods based on RMSE for out-of-sample one-step-ahead forecasting.

News Shocks	Model	Total Arrivals	Singapore	Indonesia	China	Thailand	South Korea	Japan	Australia	UK	USA	Mean Theil-U	Rank
KLCI	GARCH (1,1)	0.757	0.938	0.948	0.633	1.004	0.840	1.025	1.258	1.029	1.056	**0.949**	**2**
	EGARCH(1,1)	2.393	2.114	0.912	0.779	2.827	0.943	1.965	1.159	0.570	1.219	1.488	15
	GJRGARCH(1,1)	0.804	1.251	0.927	0.642	1.049	0.897	1.065	0.974	1.107	0.957	0.967	7
DXY	GARCH(1,1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	8
	EGARCH(1,1)	2.502	1.562	0.996	0.622	2.461	0.934	1.019	1.116	0.754	1.259	1.322	12
	GJRGARCH(1,1)	0.892	0.898	0.872	0.736	1.000	1.008	1.038	0.981	1.067	1.114	0.961	6
S&P500	GARCH(1,1)	1.012	0.916	0.872	0.623	1.051	0.856	1.008	0.989	1.119	1.064	**0.951**	**3**
	EGARCH(1,1)	2.640	2.178	0.923	0.741	1.863	0.910	2.207	1.193	0.906	1.076	1.464	14
	GJRGARCH(1,1)	0.962	0.885	0.892	0.629	1.082	0.895	1.047	0.991	1.142	1.070	**0.959**	**5**
CO	GARCH(1,1)	0.800	1.091	0.881	1.170	2.233	0.847	1.479	0.992	0.972	0.986	1.145	11
	EGARCH(1,1)	1.784	1.562	0.901	0.669	1.799	0.891	2.557	1.107	0.795	1.464	1.353	13
	GJRGARCH(1,1)	0.824	1.145	0.875	0.826	1.662	0.840	1.497	0.982	0.501	0.896	1.005	9
GP	GARCH(1,1)	0.829	0.925	0.898	0.623	1.054	0.849	1.008	0.987	1.168	1.054	**0.940**	**1**
	EGARCH(1,1)	0.993	1.161	0.872	0.618	1.014	0.912	2.216	1.077	1.230	1.084	1.118	10
	GJRGARCH(1,1)	0.774	0.841	0.877	0.630	1.315	0.885	1.044	0.991	1.201	0.993	**0.955**	**4**

7. Conclusions

This study was conducted with the objectives of first explaining the concepts of primarily volatility models with combined multiple financial news shocks, as well as the news impact curve, and then adapting those concepts in order to investigate the symmetric and asymmetric effects on the volatility of tourism demand in Malaysia. The findings of this investigation are summarised in five primary findings.

First, it was discovered that conditional mean equations had a monthly seasonality. This implies that the number of international visitors that arrive in Malaysia varies from month to month according to seasonality.

Second, it was demonstrated that news shocks had a long-lasting impact on the number of monthly tourist arrivals in Malaysia, with a quadratic relationship between the two variables. The news impact curve is quadratic and centred on ε^2_{t-1} because the conditional variance of the GARCH model depends solely on the square of the unexpected news shocks. In summary, if the squared gap widens, future tourism demand is anticipated to become more unpredictable and difficult to predict.

Another conclusion of this study was the validation of an earlier discovery that the GARCH model has a tendency to overestimate variance when $\varepsilon_{t-1} > 0$, and a tendency to underestimate variance when $\varepsilon_{t-1} < 0$; So, a single negative shock will cause significantly more volatility than a single positive shock of equal magnitude. As a result, the GARCH model will become substantially more crucial to decrease the portion of the volatility after negative news while overvaluing the volatility component following positive news. In contrast, the typical GARCH model tends to underestimate volatility after a huge shock and overestimate volatility after a minor shock if larger shocks generate more volatility than can be accounted for by a quadratic function. Consequently, the GARCH model revealed its limitations by failing to account for the asymmetry and leverage effects.

Third, examining the EGARCH model and the GJRGARCH model, respectively, revealed the existence of an asymmetry effect. In other words, Malaysia's monthly visitor demand volatility varies based on the type of news shock. In the models, leverage effects were also seen, as was the case previously. Monthly inbound tourism demand in Malaysia fluctuated more after negative news shocks than after positive news shocks, indicating that the latter was more unstable. Significantly, whether the news shocks were positive or negative, the GJRGARCH model showed a superior ability to predict the volatility of monthly visitor arrivals into Malaysia. This was the case irrespective of whether the news shocks were positive or negative.

Fourth, the comparison of the accuracy of forecasting for three volatility models with five financial news shocks, the performance of the GJRGARCH models, and the performance of the GARCH and EGARCH models are reviewed in the fourth section. Thus, the GJRGARCH models have a greater ability to anticipate Malaysia's monthly tourist demand volatility than other models. In terms of the five financial news shocks, the KLCI and the price of gold have the most impact on Malaysian tourist arrivals.

Fifth, the conditional volatility increased much higher in the presence of a significant positive shock than in the absence of a significant positive shock (or vice versa). In other words, the effect of a large, positive, fresh shock on tourism demand is expected to be greater than the effect of a modest, positive shock. The leading hospitality and tourism companies will unquestionably profit if they are able to capitalise on the potential for a substantial increase in revenue resulting from an increase in the number of people who travel and the amount of money they spend on a variety of travel products and services.

As a result of these findings, it is evident that the Malaysian government and key stakeholders within the tourist industry should pay special attention to the considerable and frequently unusual changes in the tourism sector that occur during the live transmission of negative news. A negative shock raises conditional volatility more than a positive shock. Negative shocks, on the other hand, are difficult to predict since they occur irregularly and abruptly. This demonstrates the importance of preparing accurately and thoroughly for the inevitable occurrences of negative circumstances. A drop in tourist demand could

negatively impact tourism enterprises, groups, and associations. Tourism enterprises, organisations, and associations must adopt business plans to counteract the negative effects of a predicted decline in tourism demand.

Tourism crisis management necessitates corresponding evaluation, preventive, and treatment work for the Malaysian tourism business and a news shock forecasting project. First, the government of Malaysia will alleviate the industry's difficulties. Faced with various news shocks, the Malaysian government can assist cultural and tourism businesses in resuming work and production on multiple levels, including policy interpretation and implementation, strengthening financial support, optimizing government services, and subsidising online services. In light of the difficulties inherent in the industry's development, it is recommended that the government implement a more comprehensive tourism industry revitalization policy, provide financial subsidies for tourism services and related enterprises to resume operation and production, and provide special support for the renovation of tourism venues and facilities. Second, enhancing the function of the Malaysian Tourism Industry Association in terms of direction and oversight. The industry's passivity caused by news shocks is a short-term external shock that has little effect on the tourism industry's medium- and long-term development trends. Under the influence of diverse news, intensify the correction of the public health environment in hotels, restaurants, scenic areas, and other tourist destinations, and monitor the improvement of the service supply chain in the hospitality and tourism industries. Third, fostering the modernisation and transformation of Malaysian business services. A news shock is a crisis, but it may also be a chance for businesses to reform and advance. Future tourism market competitiveness will involve sales and distribution networks, intelligent process management, and enhanced service delivery, and will promote the rapid integration of emerging technologies and tourism in Malaysia, as well as enhance the value of digital culture and tourism services. Encourage more cultural and exposition venues to provide digital online exhibition resources, assist tourist attractions in developing VR/AR service functions, and accommodate the public's desire to view exhibitions and tours online without travelling. Fourth, promoting the pooling of resources and the complementarity of services among Malaysian businesses. For instance, catering businesses may collaborate with meal delivery, fresh food e-commerce, and other industries and engage in experimental cooperation in flexible employment and business collaboration. Fifth, expanding the applicability of Malaysia's tourist big data further. All localities should accelerate the interconnection of tourism data resources, form a rapid tracking of tourism flow and tourist movement trajectories, establish a tourist relationship map, precisely locate the path of the epidemic's transmission, and more effectively implement tourism "travel management" and "data decision-making". Sixth, boosting international market growth, trade, and cooperation. The Malaysian government and tourism operators should do a commendable job of bolstering the international bargaining position of businesses with international ties. Concurrently, enhance collaboration with the worldwide market, optimise the supply of tourism products, and mitigate the impact on the global economy.

Similar to other types of research, this study has some limitations. First, the news shocks method for estimating tourism demand may have a potential limitation (even if the theory has been extensively applied in the international funding domain, which is highly sensitive to international economic or financial conditions). This study indicated that tourism demand is sensitive to environmental changes. Whether the news is positive or negative, news shocks have diverse consequences on the global tourism industry. Positive news may have a lasting impact on travel demand and an immediate effect. Future research might examine the magnitude of these effects and whether they stem from the same (source) of good or bad news. In addition, the volatility models and accompanying news impact curve (NIC) are used in this paper to explore symmetrical and asymmetrical tourist effects. Future research can use time series models, econometric models, artificial intelligence models, judgmental forecasting methods, and combination or hybrid methods to assess the impact of news shocks on tourism. In the future, more news shocks, such as numerous

events, diseases, and natural catastrophes, can be used to research. This study applied monthly data; future research could utilise more frequent data, such as quarterly, cyclical, or daily data, to better comprehend how news shocks affect tourism demand. To achieve greater accuracy, it would be beneficial to comprehend the characteristics of a continually changing environment, which would include the occurrence of unplanned events, and to develop creative approaches for making more accurate forecasts. In addition, additional research to better understand the research theories in volatility models and the news effect curves would improve the long-term accuracy of tourism demand forecasting, as would more comprehensive testing of the ideas. In the meantime, the models derived from this study can be employed to forecast the volatility of tourist demand in other nations, thereby aiding in the formulation of more reasonable measures and the development of hospitality and tourism initiatives by both the government and non-government sectors in these other nations.

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