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The Volatility of the Stock Market and Financial Cycle: GARCH Family Models

(Kemeruapan Pasaran Saham dan Kitaran Kewangan: Model Keluarga GARCH)

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ABSTRACT

The paper examines the association between financial market volatility and actual economic incidents. We specifically analyze the statistical characteristics of the stock price series and its association with the financial cycle. Using 20 years of Vietnamese main stock VNIndex daily data from 2 August 2000 to 31 December 2020, we select the most adequate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models and corresponding distribution rules. The paper initially assesses several types of GARCH models' criteria, namely the log-likelihood, AIC and BIC, in choosing the best model to illustrate the financial cycle. We further use three different distribution rules, namely the normal distribution rule, the Student-t statistic distribution, and the Generalized Error Distribution (GED), in selecting the best GARCH model. The results show that Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) with student-t statistic distribution seems the best suited to demonstrate the stock price and its return volatility. It also suits the marginal distribution of the financial cycle. Our study further validates the lead time and volatility between the selected model results and the significant financial events using the turning point and Bull-Bear application (Lunde and Timmermann 2004). Although the recommended model has shown no evidence as an effective forecast tool for the financial cycle in long run, this study paves the way for extensive research in the future.

Keywords: Stock market; financial cycle; volatility; Vietnamese, EGARCH
JEL: C52, C58, G17, E32, E33, E37

ABSTRAK

Makalah ini mengkaji perkaitan di antara turun naik pasaran kewangan dan insiden ekonomi sebenar. Kami secara khusus menganalisis ciri-ciri statistik siri harga saham dan kaitannya dengan kitaran kewangan. Menggunakan data harian stok utama Vietnam VNIndex selama 20 tahun dari 2 Ogos 2000 hingga 31 Disember 2020, kami memilih model keluarga Generalized Autoregressive Conditional Heteroskedasticity (GARCH) yang paling mencukupi dan peraturan pengedaran yang sepadan. Kajian ini pada mulanya menilai beberapa jenis kriteria model GARCH, iaitu kemungkinan log, AIC dan BIC, dalam memilih model terbaik untuk menggambarkan kitaran kewangan. Kami selanjutnya menggunakan tiga peraturan taburan yang berbeza, iaitu peraturan taburan normal, taburan statistik Student-t, dan Taburan Ralat Umum (GED), dalam memilih model GARCH terbaik. Keputusan menunjukkan bahawa Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) dengan taburan statistik pelajar-t nampaknya paling sesuai untuk menunjukkan harga saham dan turun naik pulangannya. Ia juga sesuai dengan pengagihan marginal kitaran kewangan. Kajian kami selanjutnya mengesahkan masa pendahuluan dan turun naik antara keputusan model yang dipilih dan peristiwa kewangan penting menggunakan titik perubahan dan aplikasi Bull-Bear (Lunde dan Timmermann 2004). Walaupun model yang disyorkan tidak menunjukkan bukti sebagai alat ramalan yang berkesan untuk kitaran kewangan dalam jangka panjang, kajian ini membuka jalan untuk penyelidikan yang meluas pada masa hadapan.

Kata kunci: Pasaran saham; kitaran kewangan; turun naik; Vietnam; EGARCH

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INTRODUCTION

Following the judicious warning given by economist Harrison (2010) regarding the risk of cyclical fluctuations of the market during 1995-1997 (Phillip 2016), global economic experts have taken a more cautious approach to study the effects of cyclicality on sustainable growth as well as forecasting cyclicality. In early 2018, MBS Securities Company released a report entitled "*World Economic Cycles and Lessons for Vietnam*" to analyze the global economic situation and forecast the possibility of a 10-year cyclical downturn as well as identify the risks to the Vietnamese economy. Successful prediction of financial events and market volatility bring many benefits to risk assessment, asset pricing, business decision making, and prediction of financial stages/events. Therefore, academic research must apply quantitative models to illustrate and forecast the business cycle in the general and financial cycles, respectively.

The 2008 financial crisis indicated the possibility to examine the macro-financial cycle but took financial factors into account and gave rise to a contemporary concept called a financial cycle. While there is no universal definition of the financial cycle, it usually refers to the fluctuations in financial players' consciousness, perspectives, and behaviours toward financial risk throughout the economic condition and financing period up to the generation of the boom-and-bust cycle for several main financial variables. As a result, the characteristics and dependence structures of financial cycles have become a central issue in macroeconomic policy. Specifically, action has been devoted to identifying a single measure or model that summarized such indicators, thus simplifying the analysis of the financial cycle, with benefits for both fundamental risk assessment and stabilization policy.

Influential studies on the structure financial cycle via market volatility include Schwert (1989) and Chauvet et al. (2015). While Schwert (1989) investigated whether the economic factors help to explain the volatility in financial markets, Chauvet et al. (2015), Wu and Ow (2021) presented information on economic variables that help predict future volatility despite the connection between volatility and economic activity from a statistical perspective. Lijleblom and Stenius (1997) provided a comprehensive analysis to verify the reverse causality from financial market impact to the evolution of the real incidents. Plenty of academic works present a strong connection between stock market volatility and macroeconomic fundamentals (Engle & Rangel 2008; Engle et al. 2008; Diebold & Yilmaz 2010; and Corradi et al. 2013).

On the other hand, it is a popular belief that the stock prices' volatility in financial markets is a reliable indicator of the imminent stance of the business cycle and reversal. According to this position, the observed time series data seems to depend on three factors including its past value (autoregressive), the condition of the past information (conditional), and the existence of non-constant variance (heteroskedastic) (Gujarati 2011; Brooks 2014) that would commonly be covered by the Autoregressive Conditional Heteroskedasticity (ARCH) model. The findings of several studies indicated that stock market volatility evolves and fluctuates in clusters; for instance, the time series with low volatility periods and high volatility periods existing during the dynamic clustering (Chou 1988; Islam 2014; Bonga 2019; Babashova 2020). However, the ARCH model is not sufficient to consider either the leverage effect or measure cluster volatility and the distribution with leptokurtosis time series. These problems require the development of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models, including EGARCH, TGARCH (Ho et al. 2017), and GJR-GARCH (Brownlees et al. 2011; Laurent et al. 2012; Almeida & Hotta 2014). Although efforts to structure the financial cycle by employing the stock market volatility has seen good progress, there is still room for improvement.

The main motivation for this paper is that the financial cycle might be derived from market indice volatility implied by the market's expectation on future volatility. The GARCH model is popularly used as an in-sample tool to investigate the implied volatility index known as a predictor of volatility, since stock-implied volatility contains both historical volatility information and investors' expectations regarding future market conditions. Pursuing this study encourages us to collect the empirical findings to support the desire to develop a more suitable model to combine many potentially finance-related indicators and illustrate the market's uncertainty and financial cycle in Vietnam.

The other motivation for our paper is to discover a new tool to simulate and predict the financial cycle through historical stock market volatility. Building a new one is difficult; hence we explore the existing predictors that can predict financial incidents via stock volatilities and then compare their results with actual historical events to confirm the stimulation function. Although the combination with a turning point is not new because it has been well demonstrated in a series of papers by Borio et al. (2019), Ardila and Sornette (2016), and Chebbi et al. (2013), the collaboration between the GARCH model and turning point and algorithm of bull and bear phases (Lunde & Timmermann 2014) in building the financial cycle in Vietnam is rarely used. From this perspective, the combined approach is considered an important competitive advantage in this paper. Therefore, the purpose of this article is to verify whether the relative performance of the GARCH family models in estimating and forecasting volatility in the most significant Vietnamese stock exchanges over the prolonged sample period is potentially linked to the financial cycles that pave the way for a forecasting tool to illustrate the finance cycle based on stock market information.

We use daily data from the Ho Chi Minh Indices (VNIndex), a major stock market index that tracks the performance of more than 303 equities from listed corporations on the Ho Chi Minh Stock Exchange in the period from 2nd August 2000 to 31st December 2020. To eliminate the possible signal-to-noise ratio of the data, Hodrick's Prescott (HP) filter and the Christiano and Fitzgerald (CF) filter are used to minimize the quadratic form of the model and to support the segmentation process during the observed cycle.

The remainder of this study is organized into five sections following the successive section that depicts the conceptual framework and the brief literature review. While the third part reviews the used methodology and building the econometric approaches, the testing and subsequent procedure is conducted to examine the appropriate estimation of the given models in the fourth section. Finally, the empirical findings and our conclusions are given in the fifth section.

CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

CONCEPTUAL FRAMEWORK

The two conceptual frameworks, including the theory of the financial cycle and the Markov (1971) process, are investigated to address the objective of evaluating the efficiency in simulation of financial cycle as well as to provide the financial cycle forecast by employing the appropriate models.

Firstly, the hypothesis of financial fluctuations was initially released in the 1950s, yet it was not recognized and applied until the financial crisis of 2008 when the new concept of the financial cycle was first raised. Although the financial cycle definition has rarely received attention from academics, the researchers generally acknowledged that there are similarities between a financial cycle and an economic cycle during periods of expansion and contraction. According to Minsky (1992), the main mechanism that drives the economy toward crisis is the accumulation of debt by non-governmental objects. Especially, Ponzi[1] borrowers (Minsky 1975: 7) share that the appreciation of asset value is sufficient to cover refinancing, while cash flows, generated from investment activities, cannot make sufficient payment for the current debt (interest and principal). Specifically, when the increase in the stock value is insufficient to cover the refinancing of the borrower's debt, it leads to the collapse of the asset bubble and stimulates a break in the crisis. Conversely, financial cycles often reflect the characteristics of private credit behaviour or asset prices, tend to be at a peak prior to the banking crisis and financial recession, and usually cause permanent losses and long-run effects. Hence, it is more difficult to recover than the economic cycle (Borio 2014; Borio et al. 2018). The close association between the financial cycle and financial crises also provide valuable evidence to understand the significant impact that the financial cycle has on the real economy, meaning that the financial cycle is an amplified version of the real business cycle.

Certainly, the characteristics of the financial cycle are known to be identified as the financial system, the monetary policy, and the economic-institutional system. Furthermore, it is well known that stock markets play the most prominent role in a country's modern economic development. Hence, to determine the financial cycle systematically and quantify its characteristics, the price of securities is normally used as the primary data with or without several market indicators such as interest rates, disposable income, and credit growth on Gross Domestic Product (GDP) (Stremmel 2015). These factors might not necessarily depend on the period, yet they tend to rise and fall within the economic behaviour nature. However, several statistical studies show that the cyclicality that appears in the data is likely to be rejected when statistical techniques are unable to distinguish between the standard and random numbers. Thus, to standardize the data and minimize the virtuality of cyclic identification, the paper employs the quantitative framework based on the Markov process and GARCH models to limit the weaknesses of the Markov string.

Consequently, the Markov process allows modelling of the time series data by states in which each state is a deterministic probability distribution. However, one of the limitations of GARCH is that variance is a conditional event, which does not carry out an asymmetric reaction with occurred shock. Therefore, in the article, the asymmetric model (EGARCH and TGARCH) is called to address the issue and is used to describe asymmetrical phenomena. On the other hand, concerning the fluctuation of time series data, variance is hardly assumed to be constant in all cases, and the logarithm of stock prices does not follow the standard distribution. To cover the data obstacles, several distribution rules such as the Student-t statistic distribution rule and GED distribution should be combined with the selected GARCH model to efficiently measure and predict the variation.

LITERATURE REVIEW

Recently, researchers and practitioners have conducted an investigation of modelling and forecasting the volatility of stock markets as well as identifying the cyclical stages based on the built model. Several topics focused on identifying the financial cycle or measuring its impact on the market and applying forecasting models such as the cycle index (Kamada & Nasu 2011; Li et al. 2020; Miranda-Agrippino & Rey 2020; Challoumis 2021), the specific cycle dating algorithm (Harding & Pagan 2002; Borio et al. 2018, 2020; Kumar et al. 2020; Camacho et al. 2021), or the Financial Stress Index (Slingenberg & De Haan 2011; Oet et al. 2015; Monin 2019; Ishrakieh et al. 2020; He et al. 2021; Rezagholizadeh et al. 2021). The most favoured financial indicators that showed high accuracy are stock prices, stock market volatility, real estate prices, and credit scale. The nearest papers such as Li et al. (2020); Miranda-Agrippino and Rey (2020); Challoumis (2021) provide the empirical evidence for the possible connection between the financial cycle with other factors such as monetary policies, between high end economics and developing ones. Others including Ishrakieh et al. 2020; He et al. 2021; Rezagholizadeh et al. 2021 focus on the energy stock and national currency value's impact on the financial stress in several regions such as Iran, Lebanon, the United States and Europe. However, due to the non-heterogeneous lag of a cycle, the selection mechanism of variables and the discrete information lead to difficulties in identifying and forecasting the financial cycle, thus impairing the popularity of the financial cycle theory as well as its feasible prediction function. Therefore, to cover the full theoretical foundation for the application of the analysis, this paper requires two fundamental systems, including the time series models of the financial cycle and the cyclic identification theory.

In terms of the variable for financial cycle studies, time series data that relate to the market such as credit scale, oil price real estate prices, stock prices, and index volatility are employed to illustrate the volatility cycle or financial cycle. According to Appendix 1, summarized researched methodology and corresponding papers, the stock market volatility is one of the most favoured indicators that were employed by a series of macroeconomics including the Dynamic model (Cevik et al. 2016; Aboura & Roye 2017), the Principal Component Analysis (PCA) model (Dahalan et al. 2016), and Equal weighting (Duca & Peltonen 2015; Zigraiova & Jakubik 2017). That is due to the fact that stock volatility is the indicator toward countercyclical, and it might be linked to the volatility predictability (Christiansen et al. 2012). In Vietnam, even fewer articles examine the volatility of securities price to explain the phases of the financial cycle, regardless of its popularity in foreign research. VNIndex is a popular stock index showing the trend of market capitalization price movement, so it can both reflect capital flow (through the volume of listed shares) and show investors' sentiment, stock market performance, and fluctuations in the Vietnamese economy.

Concerning the financial cycle identification scope, a range of founded theories are highlighted, such as the history of the economy (Niemira & Klein 1994), the real business cycle (King et al. 1991), the time series spectrum analysis model (Baxter & King 1999), and finally the two-phase financial cycle (Terrones et al. 2011). However, those theories provide only a basic explanation for the formation of a financial cycle phase, and their general characteristics, most of which are qualitative through empirical observation, rarely help to forecast or measure the impact. Although several macroeconomic prototypes are reviewed to investigate the financial cycle including Real Business Cycle through Vector autoregression (VAR) model (Jawadi et al. 2021), Financial Stress Index by Principal Component Analysis (PCA) model (Ishrakieh et al. 2020), and Trend-cycle decomposition based on Dynamic model (Krustev 2019), they fail to capture microfoundations and a key aspect of economic behaviour such as stock volatility, which is the required alternative quantitative method that may be more useful in understanding financial cycle. The prediction model of Lawrence Klein (1980) is one of the first comprehensive econometric models for forecasting cycles. Supporting by various theoretical studies, Klein presented three main models under the assumption of commodity consumption, including the two factors of product production and labour, the cash balance model, and the structural model. They were developed based on the annual economic data of the United States during the 1921-1941 period. In particular, the large structural model is the most fundamental research in the forecasting system, with 16 equations, 16 endogenous variables, and 13 exogenous variables describing the cyclical trends. Applying Klein's quantitative studies, Harvey and Jaeger (1993) built ARIMA-based financial forecasting models. Since the signal-to-noise tightness was initially assumed to be fixed data in "*Modeling the Business and Financial Cycles in a Multivariate Structural Time Series Model*" (De Winter et al. 2017), the upgraded models were introduced by adding the highest signal-to-noise ratio.

While these studies interpreted and illustrated cycles as in the growth and decline trend, the randomness of disturbance cannot be discerned. According to the probability and statistics theory, the marginal distribution of a set of data is the probability distribution of the random variables in that subset (Dekking et al. 2005). According to Sismondi's Periodic Crisis Theory and NBER's biphasic business cycle, the economic cycle is the natural fluctuation of the economy between periods of expansion (growth) and contraction (recession). For each period, each model assumes that the index will drift upward due to the common expectations of market participants. But the index will shift (up or down) by a random shock, which will simulate the standard deviation resulting in an expansion of the standard deviation. Therefore, models belonging to the ARCH group – a measure that considered the historical aspect of self-regressive conditional change variance are more suitable for illustrating the nature of financial cycles. Especially, GARCH family models including EGARCH, TGARCH, GJR-GARCH, and PARCH have been continuously promoted to describe the marginal distribution of financial assets (Jiang et al. 2019; Kotkatvuori-Örnberg 2016; Shahzad et al. 2019). Therefore, the paper uses GARCH group models with conditional variance, illustrating the change in the transformation process better than other models (Lamoureux & Lastrapes 1990; Hansen & Lunde 2005). Accordingly, the EGARCH model tends to observe the asymmetrical responses of volatility to positive and negative shocks, so the GJR-GARCH model is asymmetric to describe the marginal distribution, taking into account asymmetrical effects. The normally distributed GARCH model not only describes some important stylized events of financial returns but also to remove the serial dependence in the component time series (Ali 2013). The TGARCH and GJR-GARCH models can also unwind the linear limit on conditional variance dynamics (Wu 2011).

In this article, the author takes two classes of the range-based volatility models. The first one is the traditional GARCH and its extensive version models such as TGARCH, EGARCH, and GJR-GARCH combined with various distribution rules to identify the most appropriate model to investigate the stock volatility and its returns GARCH-type models to achieve better forecasts and persistence reduction. Furthermore, filters such as Hodrick-Prescott filtering (HP filter) and the Christiano and Fitzgerald (CF) filter help examine whether financial fluctuations provide any information about the upcoming variance at a certain level of economic activity. Considering the scope of the study, the article only refers to the depiction of the GARCH family model, without explaining the cause and the cyclical fluctuations in detail.

RESEARCH METHODOLOGY

DATA AND PRELIMINARY STATISTICAL ANALYSIS

Our empirical analysis of the link between the stock market volatility and the real financial cycle uses the daily closing Vietnam Stock Index, known as VNIndex, for the period from August 2, 2000, to December 31, 2020, which is collected via the website Investing.com. Specifically, the sample of 4944 observations is employed to measure the situation on the stock model. Furthermore, in order to remove the differences in the index's actual value or generating the stop over-time series, P_t is defined as a VNI-converted index by logarithm, P_t = log (*VN Index*). The VNIndex returns/growth rates are modeled as $r_t = \log(p_t) - \log(p_{t-1}) = \log\left(\frac{P_t}{P_{t-1}}\right)$. Furthermore, the volatility of thgrowth rates is evaluated using the following formula:

$$Var(r_i) = E(r_t - E(r_t))^2$$

Daily data is used to compute the variance in this article and then the second term: $E(r_t) \approx 0$. Therefore, it can be dropped from the computation, which yields: $Var(r_i) = E(r_t)^2$. Therefore, the volatility of the growth rates is evaluated by the square of its value, r_t^2 (Flury, 2013). Figures 1A and 1B illustrate the VNIndex volatility and its return over the researched period.

According to Figure 1A, both the high-oscillation cluster phase and low-oscillation cluster period exist, which appear to be self-correlated, meaning that, as long as the volatility fluctuates to either dire, high, or low, this trend remains for a certain period. This heuristic idea underlies the ARCH model (Gujarati 2011).

As can be seen from the above Figures 1A and 1B, periodic fluctuations arise during the observed period, and their density characteristics can cause difficulty identifying the turning points and trends long term. Therefore, to simplify volatility, minimize short-term random steps, and accurately determine the real market financial cycle (actual growth) through VNIndex growth rates with long-term growth lines (trend growth), the article uses the Hodrick-Prescott filtering (HP filter) method for the GARCH model. This model has the most suitable distribution rule with the knowledge that the HP filter itself might make it easy to generate fake effects in the data processing process and pose a big risk in forecasting (Hamilton 2018). To limit the disadvantage of the HP filter and improve the quality of cycle forecast results of the GARCH model, Christiano and Fitzgerald (CF) filters will also be used in parallel. Finally, to simulate the GARCH model result and link with the financial cycle, this article examines the turning points, whose literature review was based on the bull and bear phases of the stock market and the algorithm of Lunde and Timmermann (2004). The bull and bear phases of the stock market are representative for the periods which include either the gradual or sharp fluctuations of a few market indexes, this is the same as the bottom and the peaks of a financial cycle.

Figures 2A and 2B examine the range of statistical properties of the abovementioned data. In these figures, the mean value (0.000366) of VNIndex returns is almost zero, while its Standard Deviation (0.0011) is far from 1, thus supporting the fact that stock returns do not follow the normal distribution rule. Furthermore, the negative skewness (-0.2962) depicts that the data is left skewed, and the skewness is in the range of -0.5 and 0.5, meaning that the data are nearly symmetrical. In addition, with a value of 6.6261, the Kurtosis of the series of VNIndex return is Leptokurtic, indicating the high chance of an outliner. Jarque-Bera's statistics gain a high enough value (2781) to reject the sequence of data with normal distribution at a significance level of 1%. In addition, the Q-statistic Ljung-Box validation of the correlation has also supported the assumption of the existence of a data chain. Therefore, the preliminary statistical analysis suggests that the Autoregressive Conditional Heteroscedastic (ARCH) process should be employed to examine the variation over time and justify the deviation from the return's series. Specifically, when the ARCH model is higher than ARCH (3), the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986) then should be used. It allowed us to consider the past conditional variance in the current ARCH equation and is a popular volatility model due to its flexibility and accuracy in modelling stylized facts such as leptokurtosis and volatility clustering.

FIGURE 1A: VNIndex volatility from 02/08/2000 to 31/12/2020
**Source:* Investing.com

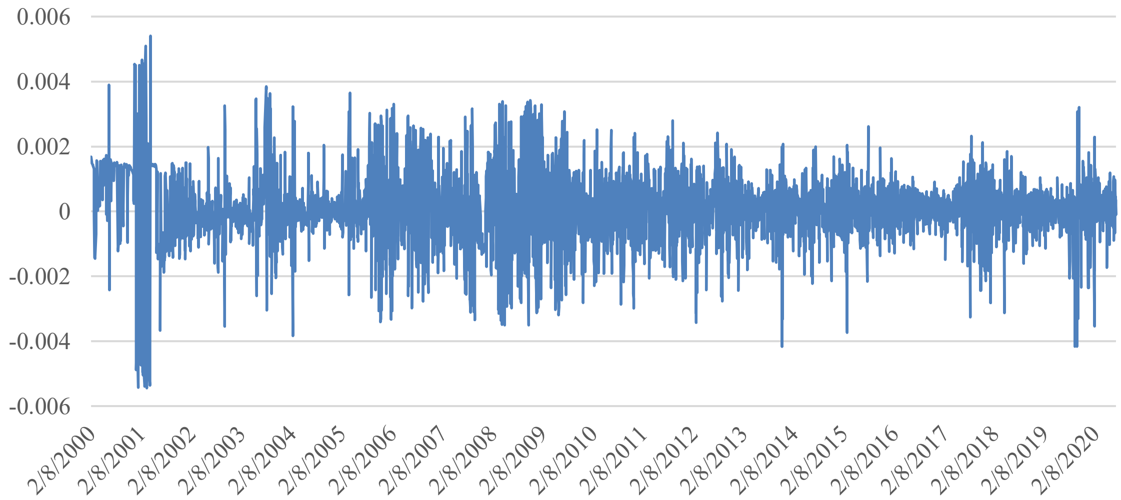

FIGURE 1B: Growth rate of VNINdex from 02/08/2000 to 31/12/2020

TABLE 1. Result of Unit Root Tests Using Augmented Dickey Fuller (ADF)

		At level	At 1st Difference	Result	Prob.*
	Test critical values	-23.07	-26.11		0.00
r	1% level	-3.43*	-3.43	I(0)	
	5% level	-2.86**	-2.86		
	10% level	-2.57***	-2.57		
		-8.53	-28.76		0.00
r^2	1% level	-3.43*	-3.43		
	5% level	-2.86**	-2.86	I(0)	
	10% level	-2.57***	-2.57		

Note: *MacKinnon (1996) one-sided p-values.

Table 1 provides the stationary test results to ensure a stable data series. Lags are selected automatically using the Schwarz Information Criterion (SBC) in which *, **, and *** denotes rejection of the unit root at the 1%, 5%, and 10% levels, respectively. The sample period used is from August 2000 to December 2020 in Vietnam. The ADF statistics compared with MacKinnon (1996) show that both the data of VNIndex return and growth rates have a unit root, which is equivalent to the stationary test with a significance of 1%. It is confirmed that the VNIndex growth rate is a stopped string. The stoppable characteristic of the data will help to generalize the analytical results at different stages providing the ground for further conclusion in terms of the periodicity of financial fluctuations. Furthermore, employing the GARCH family model to investigate the historical VNIndex data that contributes to the estimation of the future trend is to overcome a rogue or backward regression when using continuous random processes like the Brown or Weiner protocols (Tran & Hoang 2018).

EMPIRICAL MODEL

To assess the volatility of thtione VNIndex' growth rate with the abovementioned characteristics, the Maximum Likelihood Estimation (MLE) is a common method for estimation of the Generalized Autoregressive Conditional Heteroskedasticity model, and the GARCH (p, q) model is defined as follows:

$$r_t = u_t + \varepsilon_t$$

$$\varepsilon_t = z_t \sigma_t,\ z_t \sim iid\ F(0,1)$$

In which u_t is the conditional expectation of the growth rate and is defined by $E(r_t\,|I_{t-1})$, while I_{t-1} is the information set available at time *t–1, and* z_t is the sequence of randomly distributed variables, which are independent from the expected value and its maximum variance is 1. ε_t represents the standardized residuals:

$[\varepsilon_t] \sim$ *i.i.d* (Independent and identically distributed random variables)

$$E[\varepsilon_t] = 0; Var[\varepsilon_t] = 1$$

F is the probability distribution function for $[\varepsilon_t]$ with the normal distribution (0,1)

σ_t^2 is the conditional variance of the growth rate r_t and is calculated by the random process with the variance of conditional self-regression, GARCH (p, q) as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

The covariance stationary is $\sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 < 1$.

Ω is the division coefficient of conditional variance. The coefficient α contributes to the determination of σ_t^2, while the coefficient beta measures the shock effect σ_t^2.

In addition, to assess the leveraged effect and measure the cluster volatility and the leptokurtic distribution with the VNIndex's growth rate time series, the extended editions of GARCH model, including EGARCH, TGARCH, and GJR-GARCH, are used and defined as follows:

$$r_t = u_t + \varepsilon_t$$

$$\varepsilon_t = z_t \sigma_t,\ z_t \sim iid\ F(0,1)$$

EGARCH:

$$ln\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} \beta_j ln\sigma_{t-j}^2 \tag{2}$$

TGARCH:

$$\beth_t^2 = \omega + \sum^{p} \left(\alpha_i |\varepsilon_{t-i}^2| - \gamma d_{t-i} \varepsilon_{t-i}^2\right) + \sum_{j=1}^{q} \beta_j \beth_{t-j}^2 \tag{3}$$

GJR-GARCH:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i \left|\varepsilon_{t-i}^2\right| - \gamma d_{t-i} \varepsilon_{t-i}^2) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{4}$$

In which

u_t is the conditional expectation of the growth rate,

z_t is the sequence of randomly distributed variables,

σ_t^2 is the variance of the conditional variance of the growth rate r_t, and

ω is the division coefficient of conditional variance,

$\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{\pi}{2}}$ the parameter that takes into account the absolute value of the last period's volatility shock, which replaces the regular ARCH term.

γ_i is the calculation of disproportionate or leverage component, tested by hypothesis

$\gamma_i < 0$. The effect is worthy if $\gamma_i \neq 0$,

d_{t-i} is dummy variance, with $d_{t-i} = \begin{cases} 1 if\ \varepsilon_{t-i} < 0 \\ 0 if\ \varepsilon_{t-i} \geq 0 \end{cases}$

ב is the standard deviation of the conditional variance of the growth rate r_t

In order to support the selection of the appropriate application for modelling the financial cycle, this article also employs the value of log-likelihood (Ando 2010), Akaike Information Criterion (AIC) (Kass & Wasserman 1995; Burnham & Anderson 2002) and Bayes Information Criterion (BIC) (Schwarz 1978; Zhang et al. 2019).

Furthermore, we operate under the assumption that the distribution rules of the disturbance variable, ε_t, and the logarithmic function of $\{r_t(\theta)\}$. for the observed *T* sample are different. Therefore, the most suitable GARCH model is also estimated by three distribution rules as below:

Where z_t follows the standard distribution rule:

$$L_T(r_t|\omega,\alpha,\beta) = -\frac{1}{2}\left[Tln(2\pi) + \sum_{t=1}^{T} z_t^2 + \sum_{t=1}^{T} \ln(\sigma_t^2) \right] \tag{5}$$

where $\theta = \{\omega, \alpha, \beta, v\}$. is the vector parameter of the GARCH – normal model to be estimated.

Where z_t obeys the standard student distribution rule with a degree of *v*:

$$L_T(r_t|\theta) = T\left[ln\gamma\left(\frac{v+1}{2}\right) - ln\gamma\left(\frac{v}{2}\right) - ln[\pi(v-2)] \right] - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+v)\ln(1+\frac{z_t^2}{v-2}) \right] \tag{6}$$

where θ = {ω, α, β, v} is the vector parameter of the model GARCH - t that needs to be estimated.
v is the degree of freedom with the probability density function, defined by the function $\gamma\left(v\right)=\int_0^{\omega}e^{-x}x^{v-1}dx$.

The condition for the yield curve to follow the Student-t rule is its excess kurtosis $3(v - 2)/(v - 4)$, which exists with $v > 4$. The larger the value of v, the higher the density function of the yield curve appears, which is in line with the shape of the normal distribution rule.

Where z_t follows the Generalized Error Distribution (GED) rule with a degree of freedom v:

$$L_T\left(r_t|\omega,\alpha,\beta,v\right)=\sum_{t=1}^{T}\left[ln\left(\frac{v}{\lambda}\right)-\left|\frac{z_t}{\lambda}\right|^v-\left(1+\frac{1}{v}\right)\ln\left(2\right)-ln\gamma\left(\frac{1}{v}\right)-\frac{1}{2}\ln\left(\sigma_t^2\right)\right] \tag{7}$$

Where $\lambda=\left[\frac{2^{\left(-\frac{2}{k}\right)}\gamma\left(\frac{1}{k}\right)}{\gamma\left(\frac{3}{k}\right)}\right]^{1/2}$; θ = {ω, α, β, v}, the parameters of the GARCH-GED meed to estimate γ $(\cdot)$ as the Gamma function, and v is the free parameter representing the distribution shape of the interest rate. Hence,

$v = 2$ indicates that the law of GED distribution becomes the standard distribution re;
$v > 2$ indicates that the shape of the yield curve is lower than the shape of the normal distribution rule, while
$v < 2$ suggests a higher shape.

At the same time, the estimation method employed to quantify the difference between real growth rate r_{t+1}^2 and estimation of variance $\widehat{\sigma}_{t+1}^2$. at time t confirms the GARCH model under three different criteria including the log likelihood, AIC, and BIC.

The algorithm of Lunde and Timmermann (2004) regarding a minimum on the price change between the bull and bear markets is implemented in the following manner: the maximum value of P on the time interval $[t_{0,} t]$:

$$P_{t_0,t}^{max} = \max\ \{P_{t_0}, P_{t_{0+1}}, \ldots, P_t\}$$

With P_t as the stock market price at the time t, assuming that a base in P has happened at time $t_0 < t$. This means the same as a bull state beginning from time t_0+1. The (contrary to the) relative change in P where $P_{t_0,t}^{max}$ are used as a reference value:

$$\delta_t = \frac{P_{t_0,t}^{max} - P_t}{P_{t_0,t}^{max}}$$

Denote by λ_1. the scalars recognizing the movement threshold in stock price that makes a transformation fm a bear state to a bull state, and λ_2. indicates the reverse trend (from bull state to bear state).

If $\delta_t > \lambda_2$, a new peak is noted at the time t_{peak} with $P_{t_{peak}}$. getting a maximum o$[t_{0,} t]$. The period $[t_0+1, t_{peak}]$ is considered a bull state, and t_{peak} +1 is the time when a bear state begins. In contrast, at time $t_0 < t$, the minimum value of P on the time interval $[t_{0,} t]$ and the relative change in $P_{\min}$ can be detected by:

$$P_{t_0,t}^{min} = \min\ \{P_{t_0}, P_{t_{0+1}}, \ldots, P_t\}$$

$$\delta_t = \frac{P_t - P_{t_0,t}^{min}}{P_{t_0,t}^{min}}$$

When $\delta_t > \lambda_1$, a new bottom is noted at the time t_{trough} at which $P_{t_{through}}$ gets a minimum on $[t_0, t]$. The period $[t_0+1, t_{trough}]$ is seen as a bear state, and t_{trough} +1 is the time when a bull state begins.

RESULTS

To analyze the volatility of the VNIndex and its returns as well as select the most appropriate model to illustrate the financial cycle, all 4944 observations from August 2, 2000 to December 31, 2020 are examined and fo mentioned GARCH family models result in statistical significance at 5%.

Table 2 describes the estimated coefficients and standard deviations from the four models with statistical significance at 5%. In the GARCH (1, 1) Normal model, the estimated coefficient β_1 explains that 60% of the variation of the growth rate series at time t will affect the variation at time $t+1$, while the coefficient α_1. eals 0.15, meaning that only if the rate increases, the variance of the rate series at time $t+1$ will be affected by 15%. Those two estimated coefficient ratios β_1. and α_1 vary in the remaining three models, in which TGARCH and GJR-GAR indicate the higher impact on the growth rate and its variance then GARCH – Normal mode. In terms of the estimation of γ which reflects the leveraged effect to the growth rate, the EGARCH model produced the highest sonγ (0.942) compared with TGARCH and GJR-GARCH models' γ, at (0.0076) and (-0.2772), respectively.

From the log-likelihood approach and the AIC and BIC perspective, the EGARCH model appears to be superior, since it gains the highest log-likelihood value and the smallest one in AIC or BIC. Due to the excessive favor in selecting the parameterized models, taking the likelihood model as the sole factor to determine the model might come with the uncertain-correct answer (Gelfand & Dey 1994). Hence, the best model should be determined by an AIC score (Akaike 1973): $AIC=2K-2\log\left(\mathcal{L}\left(\hat{\theta}\middle|y\right)\right)$, where K is the number of estimable parameters (degrees of freedom) and $\log(\mathcal{L}(\hat{\theta}|y)$ is the log-likelihood at its maximum point of the estimated model. The AIC also minimizes the maximum possible risk infinite sample sizes, while the value of BIC helps to select the appropriate mol ae sample size grows, as long as the appropriate model is among the candidate models being considered (and other assumptions) (Vrieze 2012). Therefore, the EGARCH model would be further examined under three distribution rules including normal distribution, Student – t Stat distribution, and GED.

The estimation of v indicates the density function of the growth rate sequence in comparison to the location of the normal distribution shape. The higher the value of v, the farther the density of model shape is spotted compared to the normal distribution shape location. According to Table 3, the Student-t statistic distribution rule results in a higher v (0.0665) compared to GED distribution v (0.0509). Hence, the normal distribution seems to produce the density function of the VNIndex return converging nearest to the normal distribution. Furthermore, according to the log-likelihood and the value of AIC and BIC, the EGARCH (Student t-statistic) model also shows a better result than the others.

Bed on the research of Arthur F Burns (1969), an economic cycle is different from the unusual, short-term fluctuations of the trade index chain because of the synthesis and universality that takes place iall aspects of the economy. The financial cycle is an element in the economic system that can be reflected by fluctuations in specific financial indicators such as stock price or stock return. However, to meet the requirement in forecasting the components of the economic cycle or financial cycle, it is necessary to adjust seasonal factors and determine the Turning Point using the HP filter. Due to the limitations in distinguishing the true nature of fluctuations, the CF filter method is also used in parallel to consider the main trend of volatility and smooth the frequencies.

According to Hamilton (2016), the method to estimate the components of the economic cycle can be based on the OLS regression model in the form of:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h}$$

with y_{t+h} considered as a fixed coefficient, depending on the value of y_t in the preceding days and the remainder of the model representing the components of the cycle. Accordingly, the future growth rate of the VNIndex is a

TABLE 2. GARCH family models results with corresponding log-likelihood

Coefficient	GARCH (1,1) Normal	EGARCH	TGARCH	GJR-GARCH
$\hat{\omega}$	5.16e^{-13} *(0.00)*	-1.77 *(0.00)*	3.23e^{-13} *(0.00)*	1.44e^{-13} *(0.00)*
$\widehat{\alpha_1}$	0.15 *(0.00)*	-0.07 *(0.98)*	0.21 *(0.00)*	0.45 *(0.00)*
$\widehat{\beta_1}$	0.60 *(0.00)*	0.54 *(0.85)*	0.66 *(0.00)*	0.71 *(0.00)*
γ		0.94 *(0.00)*	0.01 *(0.70)*	-0.28 *(0.00)*
Log-likelihood	58780.36	59656.63	59609.42	59652.63
AIC	-23.78	-24.13	-24.11	-24.13
BIC	-23.77	-24.13	-24.10	-24.12

TABLE 3. Estimation of the EGARCH model under three different distribution rules

Coefficient	Normal	Student- t stat	GED
$\hat{\omega}$	-22.46 *(0.00)*	-25.66 *(0.00)*	-25.66 *(0.00)*
$\widehat{\alpha_1}$	-0.64 *(0.00)*	0.18 *(0.00)*	0.14 *(0.00)*
$\widehat{\beta_1}$	1.35 *(0.00)*	0.35 *(0.00)*	0.27 *(0.00)*
$\hat{v}_1$	0.14 *(0.00)*	0.07 *(0.00)*	0.05 *(0.00)*
Log-likelihood	58722.96	59269.08	59230.22
AIC	-23.75	-23.97	-23.96
BIC	-23.75	-23.97	-23.95

Markov chain that can be identified and predicted based on its adjacent past data, following the host equation:

$$\frac{dp_\alpha}{dt} = \sum_{\beta \neq \alpha} \left(k_{\alpha\beta} p_\beta - k_{\beta\alpha} p_\alpha \right)$$

In which p_α is the probability of finding a system in α state, $k_{\alpha\beta}$, $k_{\beta\alpha}$ and is the probility of transitioning from α to β and vice versa. Below is the detailed balance condition according to the Metropolis algorithm:

$$k_{\alpha\beta} p_\beta^{eq} = k_{\beta\alpha} p_\alpha^{eq}$$

Then, the probability of accepting the conversion to satisfy the detailed equilibrium will be equal to $k_{\beta\alpha}^a = \min\left(1, \frac{p_\beta^{eq}}{p_\alpha^{eq}}\right)$.

Considering a simple financial cycle according to the regular equation, the Boltzmann random particle distribution (1868) gives the probability in the form: $p_\alpha^{eq} = \frac{e^{-E_\alpha/k_B T}}{\sum_{j=1}^{M} e^{-E_j/k_B T}}$; $p_\beta^{eq} = \frac{e^{-E_\beta/k_B T}}{\sum_{j=1}^{M} e^{-E_j/k_B T}}$, with E being the potential of the particle in the external force field, k_B - constant number Boltzmann, T - absolute temperature, and M as the number of states of change.

Inferring that $\frac{p_\beta^{eq}}{p_\alpha^{eq}} = e^{-(E_\beta - E_\alpha)/k_B T} \Leftrightarrow k_{\beta\alpha}^a = \min\left(1, e^{-(E_\beta - E_\alpha)/k_B T}\right)$.

When a random error has a probability of changing the cyclic component in the range o[0, 1] is δ with a value less than the value $e^{-(E_\beta - E_\alpha)/k_B T}$, then the phase of the cycle will have a new state and vice versa, if $\delta \geq e^{-(E_\beta - E_\alpha)/k_B T}$, the cycle will maintain the old state.

δ in the canonical equation is the generalized form of the error representing the randomness of the OLS model v_{t+h}. Therefore, the variable component of the financial cycle will take the form:

$$y_{t+h} - \beta_0 - \beta_1 y_t - \beta_2 y_{t-1} - \beta_3 y_{t-2} - \beta_4 y_{t-3}$$

As mentioned, asymmetric HP filter and CF filters are used to separate the main trend and fluctuate into the cycle phase. According to Figure 3, the turning points in the two methods are similar and close to the general trend line; however, HP filters result a larger range of random error fluctuations than the CF. This is also coistent with the theoretical basis of these two filters. With the assumption that the conditional average of stock yields equazero, the obtained regression model shows that the variation in stock yield varies in trading sessions. It depends on the degree of variation on the coefficient GARCH (1) ≠ 0. Since the EGARCH (Student t-statistic) coefficient is positive, the greater the change in stock yields is, the greater the fluctuation observes.

Figure 3 illustrates several sets of times when the Vietnamese stock return most/least significantly fluctuated in a certain period such as: (1) from the second half of 2001 to the first half of 2002, (2) from the middle of 2008 to the end of 2009, (3) from the second quarter of 2014 to first quarter of 2015, and (4) from early 2020 to the end of 2020. The HP filter is designed to decompose a macroeconomic time series into non-stationary components and a static cyclical residual. The amplitude of the trend using the HP filter is higher than that of the CF filter, and the phases are more visible, but these phases' shifts are mainly due to the fact that EGARCH is inherently a causal filter (Stockhammar and Öller, 2012). Both filters are capable of permanently removing the random components of the conditional variance from the GARCH group model (Li et al. 2012). Therefore, compared to the real volatility of the VNIndex, both original data series of EGARCH (Figure 6) and the results from the HP filter and CF filter are much finer, with no obvious change or predictive characteristics as in the GARCH (1,1) models. Furthermore, the results from the HP filter are not consistent with the emerging economies; Vietnam is an example. This is because the HP filter rarely provides room for the rest of the time cycle checked to determine the presence of the cyclical component and white noise (Figure 3, recent data does not fluctuate as strongly as in the early part of the study) (Kaisser 1999; Mesentceva et al. 2014; Mezentceva & Mezthe entceva 2015).

As mentioned, the simulating ability of the EGARCH (Student t-statistic) model is suitable with the bull/bear state of finance market literature at a certain period during the fluctuation from 2000 to 2020. This article was based on the significant global and national economic events, which is considered the main factors that contributed to the significant fluctuation or gradual movement of the real VNIndex to examine the turning point of bull/bear via the application of the algorithm of Lunde and Timmermann (2004), including the US dot-com bubble (2000-2001), Oil Price Hike Incident (2004-2005), Vietnam's WTO participation (2006-2007), US sub-prime mortgage crisis (2008-2009), and the Covid-19 pandemic (2020). As a result, with the sizes of the four windows in the algorithm (τ_{window}; τ_{censor}; τ_{phase}; τ_{cycle}), the daily data frequency is calculated using function: $\tau_i^{daily} = \tau_i^{monthly} \times 21$ (assuming 21 trading days in a single month).

Table 4 provides a comparison between the turning point of stock price –VNIndex, with the result from the EGARCH (Student t-statistic) model. While the US dot-com bubble event instantly impacted the Vietnamese financial market, other internal (Vietnam's WTO participation) and external events (Oil Price Hike, US Sub-prime Mortgage Crisis, and Covid-19 pandemic) observed certain lagged months between the time event incurred and the impact on the bull/bear state. Within this state, Vietnam's WTO is a national incident which consumed a prolonged preparation and planning before the final result, hence the financial

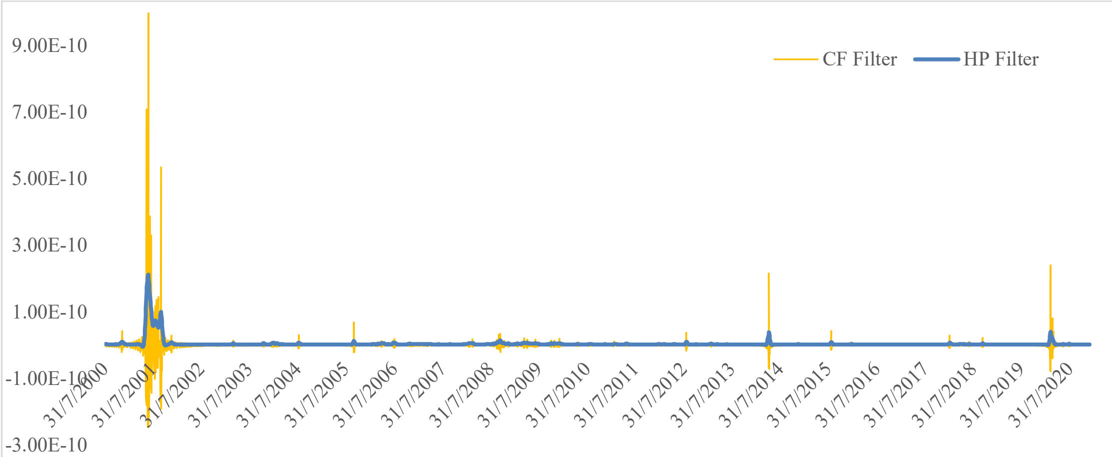

FIGURE 3. Fluctuation of growth rate of VNIndex by HP filter and CF filter

TABLE 4. Turning Points dates for VNIndex versus EGARCH Student t-statistic

Incident	Market	VNIndex	EGARCH (Student-t statictis)	Lead/Lag (months)
US Dot-com Bubble	Bull	-	-	-
	Bear	31/07/2000 - 10/01/2003	31/07/2000 - 07/02/2003	-
Oil Price Hike Incident	Bull	11/01/2003 - 04/04/2005	10/08/2004 – 18/08/2005	-20
	Bear	06/04/2005 - 23/01/2007	03/10/2005 – 13/09/2007	-6
Vietnam's WTO Participation	Bull	24/01/2007 - 02/08/2007	13/10/2008 – 08/04/2010	-21
	Bear	03/08/2007 - 22/10/2007	22/02/2011 – 27/07/2011	-44
US Sub-prime Mortgage Crisis	Bull	23/10/2007 - 05/01/2008	22/08/2012 – 04/11/2013	-60
	Bear	06/01/2009 - 20/04/2009	09/05/2014 – 15/05/2017	-66
Covid-19 pandemic	Bull	07/01/2019 – 06/11/2019	06/02/2018 – 25/01/2019	+11
	Bear	07/11/2019 – 24/03/2020	10/03/2020 – 30/12/2020	-4

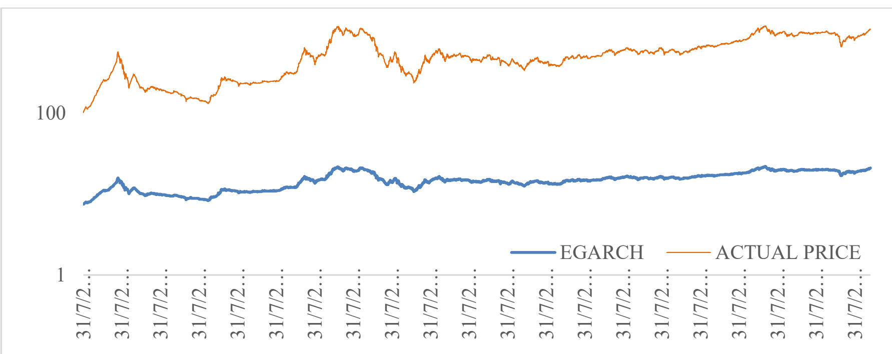

FIGURE 4. Illustration for Real VNIndex versus EGARCH Student t-statistic

market has submitted that information even 2 to 4 years beforehand. Most of the external events that affected Vietnam's financial market show a significantly large lag compared to the EGARCH illustration results, except the Covid-19 outbreak event. The reason may stem from the Vietnamese Government's early social distancing action, limiting the spread in the first waves of the epidemic, bringing expectations for a bright economic picture. However, during the prolonged epidemic situation, the mandatory social distancing has contributed to the slow-down of production, affecting the circulation of goods, investment capital, and citizens' income, leading to a downturn in the financial market. Although the results generated by the EGARCH model granted minor value, they share the same pattern as the fluctuation of VNIndex real value (Figure 4).

However, the application of the HP or CF filter on the EGARCH series reflects almost no change, due to the nature of the EGARCH model. The EGARCH model is a variant of the GARCH model that conditionally uses an exponential generalized autoregressive process. The main components of the EGARCH model include:

The GARCH polynomial, including lagged conditional variances, is recorded,

1. The ARCH polynomial, including the magnitudes of lagged standardization innovations,
2. Polynomial leverage, including lagged standardization innovations, is used to capture asymmetries in volatility subgroups, and
3. Other model components include the innovation mean model offset, a model's conditional variance constant, and the innovation distribution.

All coefficients are unknown and can only be estimated through the model or a specified parameter. Due to the lack of general statistical properties, the EGARCH model cannot derive the analysis estimating the maximum or minimum values (McAleer & Hafner 2014), but these values are signals to identify the peaks and troughs of the cycle. On the other hand, when the economic time series is not fixed, the stationary assumption can be made by calculating the difference (through the ADF and Johansen test), which might fix the non-normalities' mean while the non-normalities' variance should be handled by other methods (Stockhammar & Öller 2012). The method to deal with the variable variance is fixing the time series, eliminating the unit origin. However, extensive data series without the unit origin processed in the ARCH model shows stabilization, suggesting the possibility of a double root (Stockhammar & Öller 2012) or different integration order (Candelon & Gil-Alana 2004). Therefore, although the VNIndex series is a stationary series, EGARCH has slower volatility compared to the VNIndex series (the delay in turning points is significantly large), indicating that the data series in EGARCH could have double root or different integration order. Furthermore, EGARCH, despite the self-reflection of the asymmetry of the data series, is not sensitive to constraints, leading to the fact that positive shocks are more cyclical- destabilizing than negative turning points (Karasavvoglou et al. 2016). Although the EGARCH (Student t-statistic) model is suitable for illustrating financial cycle, it should be considered as a short- or medium-term tool rather than a predictive financial cycle or a long-term run model.

CONCLUSIONS

This paper has evaluated the daily trading Vietnamese stock price VNIndex and its return for the period from August 2, 2000, to December 31, 2020, to elaborate on the possible links between the stock market volatility and the mechanism of finance cycle by employing a wide range of academic symmetric and asymmetric GARCH family models such as GARCH (1,), EGARCH, TGARCH, and GJR-GARCH based on the normal distribution, Student-t distribution, and GED distribution together with others sub-tools including HP filter and CF filter. The examination period is around 20 years with 4944 observations, which is a sufficiently long period, including tranquil periods and significant crisis years. Descriptive statistics for the VNIndex price and its growth rate showed the presence of skewness and kurtosis and do not follow the normal distribution rule, while Q state proved that the used data is a stop string. On the other hand, within the four analysed models, three out of four (GARCH (1, 1), TGARCH, and EGARCH) indicate statistical significance with a 95% confidence level. Regarding the results of the likelihood, the AIC and BIC test revealed that the EGARCH with Student t-statistic distribution seems to be the superior model for modelling the series of logarithmic returns compared to the other three models, TGARCH, GARCH (1, 1), and GJR-GARCH with a Student-t distribution of residuals or with GED distribution of residuals.

Furthermore, the HP filter and CF filter, the most suitable model EGARCH with Student t-statistic distribution, has also been taken out the seasonal characteristic. Its results have been replicated in the form of a bull/bear state visualization through the algorithm of Lunde and Timmermann (2014), which seems in line with the national and international colossal financial incidents. However, the empirical findings indicated that there are lead times as well as certain gaps in the volatility between the estimated model result and actual event time/impact. The best model, which is relatively narrow, also failed to forecast the financial cycle or the bull/bear states for the long run. There might be several reasons for these results. With respect to the literature review model, some studies supported the disadvantages of the GARCH model, which tends to take time for the conditional variance to reach new levels (Andersen et al. 2003; Hansen & Huang 2016) and does not cover the large oscillations as the Brown simulation model (Tran & Hoang 2018). In terms of the Vietnam stock market, it would be possible to claim that financial cycles in developing countries, Vietnam for instance, might contain less significant fluctuations due to the government's strict management policies and lesser impact from overseas financial incidents. Furthermore, fluctuations in financial markets might indicate to some extent the influence of speculative indicators which might be related to other economic fundamentals such as financial policies.

In pratice, the financial system and the economy always tend to experience a crisis that normally leads to boom and bust periods. However, the predictive capability in terms of cycle time and movement of the cycle has rarely matched with the factors of the real incidents and failed to provide proper warnings or recommendations. Furthermore, most of the quantitative econometric models are extremely complex and required time resources to collect and update observed data. Therefore, based on the GARCH group model results, the author recommends that further extended studies should employ transitional dynamic models to illustrate financial cycles, the Brownian model, for example. This is because Geometric or quantum motion models (Brown model) based on Markov converters always require data normalization and uncertainty limitations, yet still stick with the phase-by-phase variation in a cycle (Tran & Hoang 2018).

On the other hand, in view of our empirical findings, the turning points might also be a promising approach to highlight a potential link between the simulation model and the real economic activity on a national level. However, the Vietnam case analysis suggests that it might be beneficial to utilize financial market return volatility as the sole key indicator of the financial cycle. This is because the economic cycle of emerging countries or the developing economies are usually synchronized as a whole, while relatively limited economic and financial divergences occur to react with the government policy implementation, leading to the amplitude and duration of the policy implementation tending to be smaller than the international ones (Burns 1969). Therefore, there is extensive room for further research on the relevance between the financial market and real economic activity and improvement in the forecasting function of the model, especially employing more relevant economic indicators or specifical explanation to shocks that cause the cyclical turning point. This article, however, focuses on the ability to simulate and forecast the financial cycle rather than analyzing the causes of the fluctuations of each phase.

END NOTE

[1] A unit engages in Ponzi finance when interest charges on outstanding debt exceed cash flows from operations. Units that construct facilities with long gestation periods or whose cash flow from operations or contracts falls short of anticipations are engaged in Ponzi finance" (Minsky 1975: 7)

REFERENCES

Aboura, S. & Roye, B. 2017. Financial stress and economic dynamics: The case of France. *International Economics* 149: 57-73.

Akaike, H. 1973. Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika* 60(2): 255-265.

Ali, S. 2013. Time series analysis of Baghdad Rainfall using ARIMA Method. *Iraqi Journal of Science* 54(4): 1136-1142

Almeida, D. & Hotta, L. K. 2014. The leverage effect and the asymmetry of the error distribution in GARCH-based models: The Case of Brazilian market-related series. *Pesquisa Operacional* (Brazilian Operations Research Society publication) 34(2): 237-250.

Andersen, G., Bollerslev, T., Diebold, F.X. & Labys, P. 2003. Modeling and forecasting realized volatility. *Journal of the Econometric Society* 71(2): 579-625.

Ando, T. 2010. *Bayesian Model Selection and Statistical Modeling*. New York: CRC Press.

Ardila, D. & Sornette, D. 2016. Dating the financial cycle with uncertainty estimates: a wavelet proposition. *Finance Research Letters* 19: 298-304.

Babashova, S. 2020. Comparative analysis of testing heteroscedasticity in nonlinear regression. *In Current and Historical Debates in Social Sciences: Fiels Studies and Analysis*. London: IJOPEC Publication.

Baxter, M. & King, R. 1999. Measuring Business Cycles Approximate Band-Pass Filters for Economic Time Series. NBER Working Paper No. 5022.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics* 31: 307-327.

Borio, C. 2014. The international monetary and financial system: its Achilles heel and what to do about it. BIS Working Papers No 456.

Borio, C., Drehmann, M. & Xia, F.D. 2018. The financial cycle and recession risk. *BIS Quarterly Review*, 59-71.

Bonga, W.G. 2019. *Stock Market Volatility Analysis using GARCH Family Models: Evidence from Zimbabwe Stock Exchange*. MPRA Paper No. 94201, University Library of Munich, Germany.

Borio, C., Drehmann, M. & Xia, F.D. 2019. *Predicting recessions: financial cycle versus term spread*. BIS Working Paper No.818. https://www.bis.org/publ/work818.pdf.

Borio, C., Drehmann, M. & Xia, D. 2020. Forecasting recessions: the importance of the financial cycle. *Journal of Macroeconomics* 66: 103258.

Brooks, C. 2014. *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press.

Brownlees, C.T., Engle, R. & Kelly, B. 2011. A practical guide to volatility forecasting through calm and storm. *The Journal of Risk* 14(2): 3-22

Burnham, K.P. & Anderson, D.R. 2002. *Model Selection and Multimodel Inference: A Practical Information – Theoretic Approach*. Berlin: Springer.

Burns, A.F. 1969. *Business Cycle in a Changing World*. Michigan: Univ Microfilms Inc.

Cevik, F., Cavas, L., Cevik, C., Derici, O., Turkmen, G., Alyuruk, H. & Gundogdu, S. 2016. Sesquiterpenoid Caulerpenyne levels of newly identified Caulepra Taxifolia VAR. *Fresenius Environmental Bulletin* 25(8): 2867-2876.

Chou, R.Y. 1988. Volatility persistence and stock valuations: Some empirical evidence using garch. *Journal of Applied Econometrics* 3: 279-294.

Chauvet, M., Senyuz, Z. & Yoldas, E. 2015. What does financial volatility tell us about macroeconomic fluctuations? *Journal of Economic Dynamics and Control* 52(2): 340-360.

Chebbi, A., Louafi, R. & Hedhli, A. 2013. Financial fluctuations in the Tunisian repressed market context: a Markov-switching–GARCH approach. *Macroeconomics* *and Finance in Emerging Market Economies* 7(2): 284–302.

Christiansen, C., Schmeling, M. & Schrimpf, A. 2012. A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics* 27(6): 956-977.

Corradi, V., Distaso, W. & Mele, A. 2013. Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics* 60(2): 203–220.

Dahalan, J., Abdullah, H.B & Umar, M. 2016. Measuring financial stress index for Malaysian Economy. *International Journal of Economics and Financial* 6(3): 942-947.

Dekking, F.M., Kraaikamp, C., Lopuhaǎ, H.P & Meester, L.E. 2005. *A Modern Introduction to Probability and Statistics*. Berlin: Springer Science & Business Media.

De Winter, J., Koopman, S.J., Hindrayanto, I. & Chouhan, A. 2017. Modeling the business and financial cycle in a multivariate structural time-series model. DNB Working Paper No.573.

Diebold, F.X., Yilmaz, K., 2010. Macroeconomic volatility and stock market volatility, worldwide. In *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle* edited by Russell, J. & M. Watson. Oxford: Oxford University Press.

Duca, M.L. & Peltonen, T.A. 2013. Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance* 37(7): 2183-2195.

Engle, R.F., Ghysels, E. & Sohn, B., 2008. *On the economic sources of stock market volatility*. Finance Working Papers No. FIN-08-043. Stern School of Business, New York University.

Engle, R.F. & Rangel, J.G., 2008. The spline GARCH model for low frequency volatility and its macroeconomic causes. *Review of Financial Studies* 21(3): 1187–1222.

Flury, B. 2013. *A First Course in Multivariate Statistics*. Berlin: Springer Science & Business Media, LLC.

Gao, Y., Zhang, C. & Zhang, L. 2012. Comparison of GARCH models based on different distributions. *Journal of Computers* 7(8): 1967-1973.

Gelfand, A.E. & Dey, D.K. 1994. Bayesian Model choice: asymptotics and exact calculations. *Journal of the Royal Statistical Society*: Series B (Methodological) 56(3): 501-514.

Gujarati, D. 2011. *Econometrics by Example*. London: Palgrave Macmillan.

Hamilton, J.D. 2018. Why you should never use the Hodrick-Prescott filter. *The Review of Economics and Statistics* 100(5): 831–843.

Hansen, P. R., & Huang, Z. 2016. Exponential GARCH modeling with realized measures of volatility. *Journal of Business & Economic Statistics* 34(2): 269–287.

Harding, D. & Pagan, A. 2002. Dissecting the cycle: a methodological investigation. *Journal of Monetary Economics* 49(2): 365-381.

Harvey, A. & Jaeger, A. 1993. Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics* 8(3): 231-247.

Ho, K.-Y., Tsui, A.K. & Zhang, Z. 2009. Volatility dynamics of the US business cycle: A multivariate asymmetric GARCH approach. *Mathematics and Computers in Simulation* 79(9): 2856–2868.

Ho, T.T, Ho, T.H. & Ngo, V.T. 2017. Modelling Stock market volatility: evidence from Vietnam. *VNU Journal of Science: Economics and Business* 33(3): 1-11

Islam, A., Islam, R. & Siddiqui, M. 2014. Stock market volatility: comparison between Dhaka Stock Exchange and Chittagong Stock Exchange. *International Journal of Economics, Finance and Management Sciences* 2(1): 43-52 .

Islam, M.A. 2014. Applying Generalized Autoregressive Conditional Heteroscedasticity models to model Univariate Volatility. *Journal of Applied Sciences* 14: 641-650.

Ishrakieh, L.M., Dagher, L., & El Hariri, S. 2020. A financial stress index for a highly dollarized developing country: The case of Lebanon. *Central Bank Review* 20(2): 43-52

Jawadi, F., Ameur, H.B., Bigou, S. & Flageollet, A. 2021. Does the real business cycle help forecast the financial cycle? *Computational Economics*. doi: 10.1007/s10614-021-10193-8.

Jiang, Y., Jiang, C.J., & Mo, B. 2019. The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. *Energy* 166(1): 577-586.

Kamada, K. & Nasu, K. 2011. *The Financial Cycle Indexes for Early Warning Exercise*. Bank of Japan Working Paper Series No. 11-E-1. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1921234.

Kass, R.E. & Wasserman, L. 1995. A Reference bayesian test for nested hypotheses and its relationship to the Schwarz criterion. *Journal of the American Statistical Association* 90(431): 928-934.

King, R., Plosser, C., Stock, J. & Watson, M. 1991. Stochastic trends and economic fluctuations. *American Economic Review* 81(4): 819-840.

Klein, L. & Young, R.M. 1980. *An Introduction to Econometric Forecasting and Forecasting Models*. Lanham: Lexington Books.

Kotkatvuori-Örnberg, J. 2016. Measuring actual daily volatility from high frequency intraday returns of the S&P futures and index observations. *Expert Systems with Applications* 43(1): 213-222.

Kumar, K., Ansari, Z.N., & Paramanik, R. N. 2020. Nexus between financial cycle and business cycle in India. *The Financial Landscape of Emerging Economies*: 15–27.

Krustev, G. 2019. The natural rate of interest and the financial cycle. *Journal of Economic Behavior & Organization* 162: 193-210.

Lamoureux, C.G. & Lastrapes, W.D. 1990. Heteroskedasticity in stock return data: volume versus GARCH Effects. *The Journal of Finance* 45(1): 221-229.

Laurent, S., Rombouts, J.V.K & Violante, F. 2012. On the forecasting accuracy of multivariate GARCH models. *Journal of Applied Econometrics* 27(6): 934-955.

Li, T., Zhong, J., & Huang, Z. 2019. Potential Dependence of Financial Cycles between Emerging and Developed Countries: Based on ARIMA-GARCH Copula Model. *Emerging Markets Finance and Trade* 56(6): 1237–1250

Liljeblom, E. & Stenius, M. 1997. Macroeconomic volatility and stock market volatility: empirical evidence on Finnish Data. *Applied Financial Economics* 7(4): 419-426.

Lunde, A. & Timmermann, A. 2004. Duration dependence in stock prices. *Journal of Businees & Economic Statistics* 22(3): 253-273.

Markov, A. 1971. *Extension of the Limit Theorems of Probability Theory to a Sum o Variables Connected in a Chain*. Reprinted in Appendix B of R. Howard. Dynamic Probabilistic Systems, volume 1: Markov Chains. New Jersey: John Wiley and Sons.

Mezentceva, O.V. & Mezentceva, A.V. 2015. Hodrick-prescott filtering of large, emerging economies and analysis of Russian GDP Growth. *Athens Journal of Business and Economics* 1(4): 287 – 298.

Minsky, H. 1992. *The Financial Instability Hypothesis* (Handbook of Radical Political Economy 74). New York: The Levy Economics Institute.

Miranda-Agrippino, S. & Rey, H. 2020. US monetary policy and the global financial cycle. *The Review of Economic Studies* 87(6): 2754–2776,

Monin, P. 2019. The OFR financial stress index. *Risks* 7(1): 25-46.

Molnár, P. 2016. High-low range in GARCH models of stock return volatility. *Applied Economics* 48(51): 4977-4991.

Nguyen, T.D. & Do, D.T. 2014. *Introduction to Financial Mathematics - Financial Mathbook*. Hanoi: Sputnik Education.

Niemira, M. & Klein, A. 1994. *Forecasting Financial and Economic Cycles*. New Jersey: Wiley.

Oet, M., Dooley, J. & Ong, S. 2015. The financial stress index: identification of systemic risk conditions. *Risks* 3(3): 420–444.

Philipp, J. 2016. Economists explain why our economy crashes every 18 Years. *The Epoch Times*.

Schwarz, G. 1978. Estimating the dimension of a model. *The Annals of Statistics* 6(2): 461-464.

Schwert, G.W. 1989. Why does stock market volatility change over time. *Journal of Finance* 44: 1115-1153.

Shahzad, S.J.H., Raza, N., Shahbaz, M. & Ali, A., 2017. Dependence of stock markets with gold and bonds under bullish and bearish market states. *Resources Policy* 52: 308-319.

Sismondi, J.C.L. 1990. *New Principles of Political Economy*. London: Routledge.

Slingenberg, J.W & De Haan, J. 2011. *Forecasting financial stress*. DNB Working Paper No.292.

Stockhammar, P. & Öller, L-E. 2012. A simple heteroscedasticity removing filter. *Communication in Statistics- Theory and Methods* 41(2): 281-299.

Stremmel, H. 2015. Capturing the financial cycle in Europe. European Central Bank Working Paper Series No. 1811.

Terrones, M., Claessens, S. & Kose, M.A. 2011. *Understanding financial cycles*. CEPR Policy Working Paper. https://voxeu.org/article/understanding-financial-cycles-0

Tran, N. & Hoang, T. 2018. Forecast economic cycle based on VNIndex with GBM. *Proceedings of 1st International Conference on Contemporary Issues in Economics, Management and Business of National Economic University*, Hanoi, Vietnam, 1072-1083.

Vrieze, S.I. 2012. Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods* 17(2): 228–243.

Wilhelmsson, A. 2006. Garch forecasting performance under different distribution assumptions. *Journal of Forecasting* 25: 561–578

Wu, L. & Ow, S.H. 2021. The Impact of news sentiment on the stock market fluctuation: the case of selected energy sector. *Jurnal Ekonomi Malaysia* 55(3): 1-21.

Wu, J. 2011. Threshold GARCH Model: theory and application. The University of Western Ontario. https://publish.uwo.ca/~jwu87/files/JobMarketPaper_JingWu.pdf.

Zhang, J. 2016. Financial cycle, business cycle and monetary policy: evidence from four major economies. *International Journal of Finance & Economics* 21: 502–527.

Zhang, X., Tao, J., Wang, C. & Shi, N-Z. 2019. Bayesian Model selection methods for multilevel IRT Models: a comparison of five DIC-Based Indices. *Journal of Educational Measurement* 56(1): 3-27.

Zigraiova, D. & Jakubik, P. 2017. *Updating the Long Term Rate in Time: A Possible Approach*. ES Working Paper No. 03. Prague: Charles University, Institute of Economic Studies (IES).

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APPENDIX A

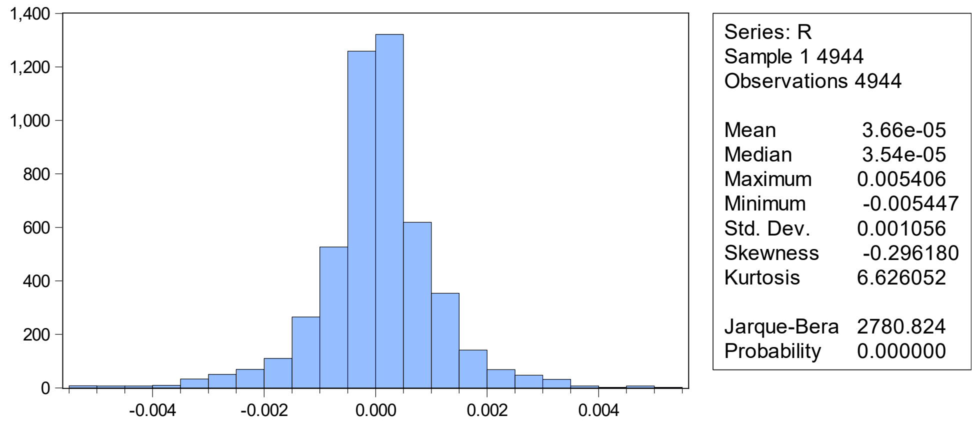

FIGURE 2A. Preliminary statistical properties of VNIndex returns/growth rates

Correlogram of R

Date: 06/04/21 Time: 15:52
Sample: 1 4944
Included observations: 4944

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.282	0.282	394.60	0.000
		2	0.061	-0.020	413.21	0.000
		3	0.024	0.013	416.08	0.000
		4	0.087	0.084	453.31	0.000
		5	0.108	0.067	511.39	0.000
		6	0.088	0.041	550.06	0.000
		7	0.055	0.019	564.88	0.000
		8	0.034	0.008	570.62	0.000
		9	0.022	-0.002	572.92	0.000
		10	0.040	0.023	581.02	0.000
		11	0.051	0.023	593.67	0.000
		12	0.018	-0.014	595.28	0.000
		13	0.045	0.040	605.30	0.000
		14	0.063	0.038	624.91	0.000
		15	0.057	0.021	640.97	0.000
		16	0.038	0.010	648.17	0.000
		17	0.029	0.008	652.22	0.000
		18	0.019	-0.004	654.06	0.000
		19	0.036	0.018	660.52	0.000
		20	0.049	0.022	672.27	0.000
		21	0.044	0.014	682.11	0.000
		22	0.034	0.011	687.90	0.000
		23	0.019	-0.001	689.60	0.000
		24	0.013	-0.005	690.38	0.000
		25	0.030	0.016	694.93	0.000
		26	0.014	-0.013	695.88	0.000
		27	0.013	0.000	696.68	0.000
		28	-0.006	-0.020	696.86	0.000
		29	-0.018	-0.023	698.48	0.000
		30	0.008	0.012	698.82	0.000
		31	0.005	-0.008	698.93	0.000
		32	0.020	0.017	700.86	0.000
		33	0.024	0.015	703.78	0.000
		34	0.022	0.010	706.09	0.000
		35	-0.001	-0.015	706.10	0.000
		36	0.012	0.010	706.79	0.000

FIGURE 2B. Correlogram of VNIndex returns/growth rates

TABLE 5. Summarized researched methodology and corresponding papers for financial cycles

Methodology	Author	Year of publication	Main Indicators/Features
Quantitative Research Methods: ARIMA, GARCH, GMM, Equal weighting, PCA, OLS Regession			
OLS Regression	Di Giovanni, Kalemli-Özcan and Ulu	2021	Corporate credit transactions; bank balance sheets
	Amiti, McGuire and Weinstein	2019	Demand/supply shocks
	Scheubel, Stracca & Tille	2019	Global Financial Safety Net (GFSN)
	Habid & Venditti	2018	Transmission channels, capital flow, asset price, monetary policy
Multi-factor predictive models	Adekoya, Ogunbowale, Akinseye and Oduyemi	2021	Stock return and oil price
A two-stage hierarchical testing	Hartwig, Meinerding and Schüler	2021	Credit-to-GDP
	Ishrakieh,.Dagher & El Hariri	2020	Financial Stress Index
	Dahalan et al.	2016	Stock market volatility and Banking sector fragility index
PCA	Cevik et al.	2013	Stock market volatility and Exchange market pressure index
	Kliesen and Smith	2010	FED rate; bond interest rate, treasury yields
	Hakkio and Keeton	2009	Bond and stock return
	Zigraiova and Jakubik	2015	Stock market volatility
	Duca and Peltonen	2013	
Equal weighting	Sandahl et al.	2011	
	Slingenberg and De Haan	2011	
	Yiu et al.	2010	
GMM, HP filter	Ma and Zhang	2016	Monetary policy, real exchange rate, long-term rate and risk premium
ARIMA Garch Copula model	Li, Zhong & Huang	2020	Financial cycle indexes
	Slingenberg and De Haan	2011	
	Oet, Dooley and Ong	2015	
	Monin	2019	
Business cycle-dating algorithm, panel probit	Borio, Drehmann & Xia	2019	Turning point, term spread, composite financial cycle indicator, debt service ratio
GARCH Midas model	Gupta & Demirer	2021	Oil market volatility
Stochastic differential equation, continuous-time auto-regressive (CAR)	Filardo, Lombardi and Raczko	2018	Inflation volatility, long term rate, NVIX
Markov-switching–GARCH, HP filter, Bry–Boschan algorithm	Chebbi, Louafi & Hedhli	2013	Turning point, investor sentiment
Nonlinear GARCH	Alqaralleh, Abuhommous & Alsaraireh	2020	Cryptocurrency
SVAR GARCH	Lütkepohl & Milunovich	2016	Macroeconomic uncertainty, industrial production, financial uncertainty
GARCH	Guerello	2016	Investors' confidence, financial uncertainty, M2, GDP, PEG
GARCH	Roy & Tiwari	2016	Stock price, IT
Macroeconomic methodology			
VAR	Jawadi, Ameur, Bigou, and Flageollet	2021	Real Business Cycle
	Miranda-Agrippino and Rey	2020	Monetary policy, economic factor; house price index

cont…

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	Miranda-Agrippino and Rey	2020	Risky Asset Prices and capital flows
	Cerutti, Claessens and Rose	2019	Capital flows
Structural Bayesian VAR	Lodge and Manu	2021	Oil prices, US equity prices relative to global equity prices, US non-energy equity prices and US long-term yields
ARMA model and VAR	Strosahl, Proaño and Wolters	2019	Frequency domain: Length and variance contribution (GDP. house price, equity, credit)
VAR and Panel Regressions	Cerutti, Claessens and Rose	2017	Capital flows
	De Winter, Koopman, Hindrayanto	2021	Macroeconomic factos, house price
	Cevik et al.	2016	Stock market volatility, Exchange market pressure index, Sovereign risk
	Aboura and Roye	2017	TED spread, stock market volatility, CDS
Dynamics model	Menden & Proaño	2017	Government bonds, interbank loans and treasury bills
	Liu, Li & Xu	2019	Spillover Index, Institutional Distance, Economic Policy Uncertainty, Bilateral Trade Intensity
	Krustev	2019	Trend-cycle decomposition (based on Laubach and Williams (2003) model)
Dynamic conditional correlations GARCH, SVAR, HP filter, CF filter	Prabheesh, Anglingkusumo & Juhro	2021	Turning point, exchange rate, domestic interest rate, Concordance index
Regressions of MP uncertainty	Lakdawala and Aeimit	2021	Exchange rate and monetary policy
Others: Conceptual, wavelet, etc.			
Conceptual research and filtration methods	Kurowski, Åukasz	2021	Credit cycle, real estate cycle, or DSR ratio
HP and band pass filter; Turning point analysis algorithm	Stremmel	2015	Credit to GDP ratio, credit growth and house prices to income ratio
Kalman filter, HP filter, cyclically-adjusted fiscal balance (based on OECD methodology)	Borio, Lombardi & Zampolli	2016	Fiscal balances, credit, property price
Continuous Wavelet Transform (CWT)	Altăr, Kubinschi & Barnea	2017	Countercyclical capital buffer, macroprudential policy
Maximum Overlap Discrete Wavelet Transform, BBQ algorithm, band-pass filters	Ardila & Sornette	2016	Turning point, uncertainty principle
The wavelet power spectrum (WPS) and the global wavelet power spectrum (GWPS)	Verona	2016	S&P500, credit, house price
Conceptual research and hypothesis	Borio	2017	Role of cycle, inflation, interest rate
	Borio	2014	Credit, GDP, property prices
	Kamada and Nasu	2011	Cycle index
	Miranda-Agrippino and Rey	2020	
Frequency and Turning point based methods	Shüler, Hiebert and Peltonen	2015	
	Harding and Pagan	2002	cycle dating algorithm
	Borio, Drehmann and Xia	2018, 2020	
	Kumar, Ansari and Paramanik	2020	

Source: By the Author