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On Volatility Spillover in the Emerging Stock Market: Asymmetric Model for Indonesia

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Negative sentiments have increased Volatility, Uncertainty, Complexity, and Ambiguity (VUCA) in global financial markets. This raises the spillover effect, in a blink of an eye, among the global stock markets, including in Indonesia. This paper provides a comprehensive assessment of the stock return volatility spillover of 11 stock markets toward Indonesia stock return volatility. Deploying the most fit stock return volatility models, this paper reveals that the volatility of the Jakarta Composite Index (JCI) return was uniquely integrated with the stock markets in the US and Asia, amidst a surprisingly strong and persistence correlation with the stock market in Thailand. In line with the significant impact of the external volatility spillovers toward the Indonesia stock market, this paper cannot find significant evidences of Bank Indonesia policy rate, inflation, and GDP growth announcements impact to stock return volatility around the announcement days.

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Keywords: GARCH asymmetric, modeling, the stock market, volatility return, volatility transmission, macroeconomic indicator announcement.

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Introduction

Negative sentiments mainly from trade war tension had increased uncertainty in global financial markets. While monetary authorities adjusted their policy interest rate, investors were responding it quickly by rebalance their portfolio, and therefore increased volatility in the financial sector. Cross country investments increase financial sector integration. In emerging markets, financial sector integration promotes financial deepening. However, it also increases domestic stock market vulnerability, since it raises global investor assets in the local market. In the Indonesia Stock Exchange, foreign investors own 45% of the total assets, with trade volume contribution around 34% (OJK, 2019).

Deploying the best fit stock return volatility models, this paper aims to elaborate the volatility transmission of the main global stock markets in both the advanced economies (the US, Japan, Korea, Singapore, and Hong Kong) and emerging markets (India, Malaysia, and Thailand) toward Indonesia stock market volatility. The volatility spillovers effect among the stock markets have been studied widely. However, the study of volatility transmission to the emerging markets, especially toward Indonesia is still limited. Zhang et al. (2019) showed strong evidence of significant volatility transmission among stock markets G20 countries. Their findings also support the geographical connection among the countries. In emerging markets, Vo and Ellis (2018) and Sari et al. (2017) found that stock return volatility of the main stock markets, the US and Asia (Singapore, Japan, and Hong Kong) influence stock markets in Vietnam and Indonesia, respectively.

Before assessing the stock market volatility transmission to Indonesia stock market volatility, this study also confirms Yalama and Sevil (2008), that stock market volatility in each market is captured the best by different GARCH asymmetric models. Using Akaike Information Criterion (AIC) this paper finds that the Threshold-GARCH (TGARCH) asymmetry model is the best model to capture stock return volatility in the US and Japan stock market, including S&P500 and Nikkei composite indices (Sari et al., 2017). However, in addition to the previous study, this paper finds that Exponential-GARCH EGARCH asymmetry model is the best model to capture stock markets in Indonesia and Malaysia, while GJR-GARCH asymmetric model is the most suite model in stock markets in Singapore and Thailand.

Since we found significant evidences of the global stock markets transmission to Indonesia stock return volatility, we further our study and examine the impact of domestic macroeconomic indicator announcements to stock return volatility. The stock markets are commonly react to the monetary policy, inflation, and Gross Domestic Product (GDP) growth announcements growth (e.g. Bomfim, 2001; Kim and In, 2002, Rigobon and Sack, 2008). However, in line with Jiang et al. (2012) and Putri et al. (2017) we cannot found the significant impact of the regular announcement of Bank Indonesia policy rate, inflation, and Gross Domestic Bruto (GDP) to Indonesia stock market return.

Using data from 2008 to 2018, this paper confirms and extends the positive association between Indonesia's stock market volatility with the US and the Asian stock market volatility (e.g. Miyakoshi, 2003; Chuang et al., 2007; Jiang et al., 2017). We show significant evidences that the US stock return indices are the leading indicators of Indonesia stock return volatility, while the Singapore, Hong Kong, and Thailand stock markets have the highest coincidence correlation with the Indonesia stock return volatility. In addition to Sari et al. (2017), our study found that Thailand stock return volatility has bigger and persistence magnitude on the Indonesia stock return volatility.

This paper different from the prior research in several ways. We investigate the spillovers effect from 11 stock markets toward Indonesia stock market volatility, including Indonesia's peer countries, such as India, Malaysia, Thailand, and South Korea (IMF, 2019). Since we can uniquely compare the impact and magnitude of the stock market volatility to the Indonesia stock market, our evidences that stock return volatility in Thailand has a bigger influence to stock return volatility in Indonesia compare to the leading stock markets in the US or Japan. Next, different from Zhang et al. (2019) and Vo and Ellis (2018) who only optimized a certain GARCH model, we use different GARCH asymmetric model that can capture the best volatility model of each market. Furthermore, we also find that domestic macroeconomic indicator announcements have an insignificant association with Indonesia stock return volatility, these provide additional evidences of the strong spillovers effects toward Indonesia stock return volatility.

The rest of the paper is organized as follows. In Section II, we discuss the theoretical framework, this is followed in Section III. by defining the data used in this study. In Section IV, we present the empirical results and some discussions. Finally, Section V provides concluding remarks and policy implication.

I. Literature Review

In a country level, one of the main concerns of the equity market study is the stock price fluctuation in a certain period or the stock price volatility. Higher stock price volatility reduces investors' ability to forecast and therefore increase risk in the stock market. In the stock market, share price movement as a whole is represented by a stock composite index, such as the Jakarta Composite Index (JCI) and the Straits Times Index (STI) in Indonesia and Singapore stock markets, respectively.

Bollerslev (1986) GARCH model commonly used to capture financial time series. However, the classical GARCH model ignores the asymmetric volatility phenomenon which is more appropriate in capturing the phenomenon of the leverage effect (Awartani & Corradi, 2005; Gokbulut & Pekkaya, 2014) or the negative correlation between volatility and return from the prior event (Black, 1976). Prior studies found that the GARCH asymmetric models are the best model to capture the leverage effect in the various stock markets (e.g.; Yalama & Sevil, 2008; Sari et al., 2017). Several GARCH asymmetric models that have been used in those studies are Integrated-GARCH (IGARCH) by Engle and Bollerslev (1986), Exponential-GARCH (EGARCH) by Nelson (1991), GJR by Glosten et al. (1993), Component-GARCH by Engle and Lee (1993), Asymmetric power ARCH (APARCH) by Ding et al. (1993), and Threshold-GARCH (TGARCH) by Zakoian (1994).

Since shocks and volatility in a capital market tend to affect or spill to other markets (King and Wadhani, 1990), Stakeholders can use a transmission shock across the market to predict a certain market behavior based on its respond other market financial behavior (Mishara et al., 2007). Therefore, prior studies try to find the transmission behavior among the stock market (e.g. Miyakoshi, 2003; Achsani and Strohe, 2006; Chuang et al., 2007; Jian et al., 2012).

The contagion effect across the global stock markets has triggered empirical studies in examining the spillovers effect. Janakiraman and Lamba (1998) mentioned the reasons of the shock transmission from a certain stock market to others: (1) dominant economic power; (2) common investor groups; and (3) multiple stock listings. Prior researches confirmed the linkages between the leading stock markets in the US, the United Kingdom, and Asia (e.g. Liu et al., 1998, Veiga & MacAleer, 2004; Achsani & Strohe, 2004). In Asia, Liu et al. (1998) found that the stock markets in Asia significantly affect each others. Using the VAR-GARCH models, Lee (2009) showed the significant volatility spillover effect among stock markets in Taiwan, Japan, Singapore, India, Hong Kong, and South Korea. It confirmed Miyakoshi (2003) that the Asian stock markets are more influenced by the Japanese stock market compared to the US stock market.

Examining the stock market spillover effect between Indonesia and Singapore with EGARCH over the period from 2001 to 2005, Lestano and Sucito (2010) showed the empirical evidences of a spillover effect from the Singapore stock market to Indonesia stock market. Furthermore, Sari et al (2017) examined the transmission of stock return volatility from several stock markets towards stock market in Indonesian. Using VAR, their findings showed that Indonesia stock return volatility impacted the most by Hong Kong and Singapore stock markets. Extending to Sari et al., 2017, this paper uses both VAR and Bivariate Granger Causality models to test the spillover effect from nine countries, including from Indonesia peer countries, such as India, Malaysia, Thailand, and South Korea.

The stock market volatility can be influenced by both the spillovers effect from other countries and domestic events, including the macroeconomic indicator announcements. Central bank policy interest, inflation, and GDP growth announcements can create abnormal volatility, since it may contain new information that has not been incorporated in the stock price (e.g. Bomfim, 2001; Kim and In., 2002; Rigobon & Sack, 2008; Jiang et al., 2012; Bernile et al. (2016). Rigobon and Sack (2008) mentioned that the event study has significantly contributed to the understanding of the monetary policy announcement impact to the stock market behavior. With the assumption that stock markets have become more efficient, researchers tend to narrow the impact of the data announcement to only a few days around the announcement date. Bomfim (2001) found that the US interest policy, Federal Funds Rate (FFR) announcements affected stock market volatility in one day window.

In addition to the interest policy announcements, inflation and GDP growth announcements have significant impact to stock market volatility (e.g. Kim & In, 2002; Kim et al., 2004;). Nevertheless, studies of macroeconomic indicator announcements on the stock market are still limited with mixed evidences in Indonesia. Bank Indonesia monetary policy rate announcements only influenced stock indices of transportation and infrastructure sectors (Putri et al., 2017). However, Andika et al. (2019) found that the Bank Indonesia policy rate and inflation announcements have a positive association with stock return volatility. Nevertheless, on a daily basis stock return volatility, Andika et al. (2019) cannot find significant evidences that GDP announcements impacted the stock return volatility.

II. Methodology

3.1. Data

The data used in this study are the daily closing price of JCI (Jakarta Composite Index) from Indonesia's stock market, and 11 total composite indices from the global stock markets. Eight of the stock markets are from the advanced economies, three from the United States INDU (Dow Jones Industrial Average Index), SPX (Standard and Poors 500 Index), CCMP (NASDAQ Index), in Hong Kong the HSI (Hang Seng Index), two from Japan, NKY (Nikkei 225 Index) and TPX (Tokyo Price Index), Singapore's STI (Strait Times Index), and South Kore, KOSPI (Korea Composite Stock Price Index). We also use three composite indices from Indonesia's peer countries, SENSEX (India Composite Stock Market Index), FBM KLCI (Malaysia's Kuala Lumpur Composite Index), and from Thailand, SET (Thai Composite Stock Market Index). All the time series are from Bloomberg, covering the period from January 2, 2008, to December 31, 2018. In addition, this paper uses the announcement date of the Bank Indonesia policy rate, inflation, and GDP growth announcements over the period of 2008-2018, from Bank Indonesia and Statistics Indonesia websites, respectively. The Bank Indonesia policy rate was BI Rate from 2008 to 2016 and it has changed to BI 7-day (Reverse) Repo Rate since 2016.

3.2. Data Analysis

3.2.1. Modeling the Volatility of Stock Index Return

The type of volatility observed in this study is stock return volatility. Awartani and Corradi (2005) defines return stock as $r = ln\left(\frac{S_t}{S_{t-1}}\right)$, where S_t is the stock price index at day t and r_t is the continuously compounded return. The stock return series from the 12 stock markets are stationary at level as it confirmed by the ADF unit root test.

The volatility model is then used to determine the best series that described the stock return volatility of each stock market. Bollerslev (1986) proposed a model *Generalized Autoregressive Conditional Geteroscedasticity* with orders *k* and *l*; GARCH (*l*, *k*), to describe volatility in a certain financial market. The GARCH model represents that *current conditional variance* also depends on *previous conditional variances* and the *lag of the* square of the remainder. The classic ARCH and GARCH models have the assumption that all the effects of shocks on volatility have a symmetrical distribution. However, the asset returns do not always have a symmetrical distribution, but also an asymmetric distribution, thus the GARCH asymmetric model represents that.

In this study, the best models in describing stock return volatility are divided into two, namely the best GARCH symmetric model and the best asymmetric GARCH model. The process of selecting the best model is combination of the orders, both orders for the ARIMA model identification conducted in this study is a combination of order p =0, 1, 2, and 3 and q =0, 1, 2, and 3, and the identification of models of ARCH / GARCH is a combination of the order k =0, 1, 2, and 3 for GARCH and l =0, 1, 2, and 3 to ARCH. ARIMA model was used as a mean model to composing the GARCH model. On each of the ARIMA model with a certain order, will obtain fifteen selection of models ARCH / GARCH. Thus, in this modeling process will get 225 model options. The best model criteria used are statistically significant for all coefficients both the coefficient on the mean model and the GARCH model. Next, the model that has the smallest AIC value will be selected. The specifications of the econometric model used in this study are the GARCH (Equation 1), EGARCH (Eq. 2), GJR-GARCH (Eq. 3), TGARCH (Eq. 4), IGARCH (Eq. 5), APARCH (Eq. 6), and CGARCH (Eq. 7).

GARCH (Bollerslev, 1986)

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i v_{t-i} + \sum_{j=1}^{l} \alpha_j e_{t-j}^2 \qquad (1)$$

EGARCH (Nelson, 1991)

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{l} \left\{ \alpha_j \frac{e_{t-j}}{\sigma_{t-j}} + \gamma_j \left(\left| \frac{e_{t-j}}{\sigma_{t-j}} \right| - E \left| \frac{e_{t-j}}{\sigma_{t-j}} \right| \right) \right\} \qquad (2)$$

GJR-GARCH (Glosten *et al.*, 1993)

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{l} [\alpha_j + \gamma_j I_{e_{t-j}<0}] e_{t-j}^2 \qquad (3)$$

$$I_{e_{t-j}}\{1;\ e_{t-j} \le 0;\ good\ news\ 0;\ e_{t-j} > 0;\ bad\ news\}$$

TGARCH; Treshold=1 (Zakoian, 1994)

$$\sigma_t = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-i} + \sum_{j=1}^{l} [\alpha_j |e_{t-j}| + \gamma_j I_{e_{t-j}<0} e_{t-j}] \qquad (4)$$

IGARCH (Engle dan Bollerslev, 1986)

$$\sigma_t^2 = \omega + \sum_{i=1}^{k} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{l} \alpha_j e_{t-j}^2 ;\ 1 - \sum_{i>1}^{k} \partial_i - \sum_{i=1}^{l} \alpha_i = 0 \qquad (5)$$

APARCH (Ding *et al.*, 1993)

$$(\sigma_t)^\delta = \omega + \sum_{i=1}^{k} \beta_i (\sigma_{t-i})^\delta + \sum_{j=1}^{l} \alpha_j (|e_{t-j}| - \gamma_j e_{t-j})^\delta \qquad (6)$$

CGARCH (Engle dan Lee, 1993)

$$\sigma_t^2 = q_t + \sum_{i=1}^{k} \beta_i (\sigma_{t-i}^2 - q_{t-j}) + \sum_{j=1}^{l} \alpha_j (e_{t-j}^2 - q_{t-j}) \qquad (7)$$

$$q_t = \omega + \rho q_{t-1} + \phi (e_{t-1}^2 - v_{t-1})$$

q_t is a permanent component of conditional variance

α_j and e_{t-j}^2 are ARCH component, β_i and σ_{t-i}^2 are GARCH component, while β_0, β_i, and α_j must be positive.

3.2.2. Cross-Correlation

Cross-correlation analysis is used to determine whether volatility stock returns from other market indices will be the leading indicators, coincident indicators, or lagging indicators of the reference series; Indonesia's volatility stock returns. Leading indicators are variables that move ahead of the reference series. Coincident indicators have the same movement as the reference series. Meanwhile, lagging indicators move to follow the coincident and reference series.

Cross correlation between two variables, say *x* and *y* can be calculated:

$$r_{xy}(l) = \frac{c_{xy}(l)}{\sqrt{c_{xx}(0)} \cdot \sqrt{c_{yy}(0)}} \qquad \text{where: } l = 0, \pm 1, \pm 2, \ldots \qquad (8)$$

$$c_{xy}(l) = \begin{cases} \sum_{t=1}^{T-1} \left((x_t - \bar{x})(y_{t+1} - \bar{y}) \right) / T & \text{where: } l = 0, 1, 2, \ldots \\ \sum_{t=1}^{T+1} \left((y_t - \bar{y})(x_{t-1} - \bar{x}) \right) / T & \text{where: } l = 0, -1, -2, \ldots \end{cases}$$

The time period used to test cross-correlations are 20 periods or one month with daily data. To be used as indicators, the criteria value of r_{xy} is the highest value during the test period.

3.2.3. Vector Autoregressive (VAR)

The VAR model in this study is used to study the spillover effect from the stock markets toward the JCI return volatility. A VAR (*p*) equations can be written as:

$$V_t = A_0 + A_1 V_{t-1} + A_2 V_{t-2} + A_3 V_{t-3} + \cdots + A_p V_{t-p} + e_t \quad (9)$$

where V_t is an *mx1* vector of jointly dependent variables – containing twelve variables, namely volatility of stock return in the market *j*, A_0 is an *mx1* vector of constant terms, A_i is *mxm* matrix of coefficients for every $i = 1, 2, \ldots, p$, and e_t is an *mx1* vector of white noise error independently and normally distributed with zero mean. The VAR model makes it possible to analyze *impulse response function* (IRF) and *forecast error decomposition variance* (FEDV).

The Unrestricted VAR model requires a data series that is stationer at the level, thus we also use the Augmented Dickey-Fuller (ADF) unit root to test the stationarity of the data. In order to determine the optimal *lag* in the VAR system (the optimal lag, *p*), we also use the smallest AIC or Schwarz Criterion (SC).

VAR model can be used for a variable forecasting, especially using information obtained from the other variables. This idea can be answered by using the bivariate Granger causality test. Thus, we also use the bivariate Granger causality test to investigate the causal relationship between two variables. This causal relationship can be tested by estimating whether one lagged variable *y* can help to forecast another variable *x*. Hereafter, we estimate the autoregressive distributed lag model (ARDL) with lag length *p:*

$$x_t = c_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=1}^{p} b_i x_{t-i} + e_{1t} \quad (10)$$

with the null hypothesis is *y* can not be considered significantly Granger-causal to x.

3.2.4. Volatility Model around Announcement Days

This paper used the model specification by Bonfim (2003) to examine the impact of Bank Indonesia policy rate, inflation, and GDP Growth announcements on stock return volatility in Indonesia, around the announcement days until three day window.

$$\sigma_t = \omega_0 + \omega_1 I_t^{(A-3)} + \omega_2 I_t^{(A-2)} + \omega_3 I_t^{(A-1)} + \omega_4 I_t^{(A+1)} + \omega_5 I_t^{(A+2)} + \omega_6 I_t^{(A+3)} \quad (13)$$

where $I_t^{(A-i)}$ is a dummy variable set to *t-i* when news released and zero elsewhere, ω_1, ω_2, and ω_3 are expected to have a negative value. While $I_t^{(A+i)}$ is a dummy variable set to *t+I* when a news is released and zero elsewhere, ω_4, ω_5, dan ω_6 are expected to have a positive value, it means that volatility increases after a news release. Dummy variables when the news is released ($I_t^{(At)}$) are not included in the model to avoid dummy variable traps.

III. Result and Discussion

4.1. The Best Fit GARCH Model

The process of selecting the best model to capture stock return volatility begins by comparing the best GARCH symmetric model (Equation 1.) and the best GARCH asymmetric model. The asymmetrical GARCH model specifications used are EGARCH (Eq.2), GJR-GARCH (Eq.3), TGARCH (Eq.4), IGARCH (Eq.5), APARCH (Eq.6), and CGARCH (Eq.7) models. Table 1. presents the results of the best symmetrical and asymmetrical candidate models of each index. It shows that the GARCH asymmetric models have a better model to capture stock return volatility than the GARCH symmetric model, as it indicated by the lower AIC value.

Each stock index has captured the *leverage* effect differently, so the best fit volatility model also varies for different stock market (Yalama and Sevil, 2008; Sari et al., 2017). The TGARCH model seems to be the best model to measure stock return volatility in the advanced economies, the US (INDU, SPX, CCMP), Hong Kong (HSI), and Japan (NKY and TPX). While the EGARCH is the best model in the emerging markets, Indonesia (JCI) and Malaysia (FBMKLCI), and also Korea (KOSPI). While, the GJR-GARCH model seems to be the best model in Singapore (STI) and Thailand (SET).

Table 1.

AIC Value of the Best Symmetric and Asymmetric GARCH Models

No.	Country	Stock Index	AIC Symmetric	AIC Asymmetric	The Best Model
1	US	INDU	-6.6553	-6.6987	Asymmetric TGARCH (2,1)
2		SPX	-6.5502	-6.6006	Asymmetric TGARCH (2,1)
3		CCMP	-6.2450	-6.2990	Asymmetric TGARCH (2,1)
4	Hong Kong	HSI	-5.9771	-5.9865	Asymmetric TGARCH (1,2)
5	Indonesia	JCI	-6.2800	-6.2868	Asymmetric EGARCH (1,2)
6	Japan	NKY	-5.8365	-5.8651	Asymmetric TGARCH (1,1)
7		TPX	-6.0100	-6.3040	Asymmetric TGARCH (1,1)
8	Singapore	STI	-6.7412	-6.7625	Asymmetric GJRGARCH (1,1)
9	India	SENSEX	-6.2530	-6.2890	Asymmetric TGARCH (2,1)
10	Korea	KOSPI	-6.4950	-6.5250	Asymmetric EGARCH (1,1)
11	Malaysia	FBMKLCI	-7.4410	-7.4540	Asymmetric EGARCH (1,1)
12	Thailand	SET	-6.4960	-6.5110	Asymmetric GJRGARCH (1,1)

Table 2. shows the estimation results of the best asymmetric model to measure stock return volatility. A positive ARCH (α) value indicates that current conditional volatility depends on news/shocks in the previous period ($t - l$). Meanwhile, a positive GARCH (β) value means that current conditional volatility depends on previous conditional volatility ($t - k$).

Table 2.

Coefficient Parameters for Best Model of Asymmetric GARCH of Each Stock Return

Country		**US**		**Hong Kong**	**Indonesia**	**Japan**		**Singapore**	**India**	**Korea**	**Malaysia**	**Thailand**
Exchange	**INDU**	**SPX**	**CCMP**	**HSI**	**JCI**	**NKY**	**TPX**	**STI**	**SENSEX**	**KOSPI**	**FMKLCI**	**SET**
Model	TGARCH	TGARCH	TGARCH	TGARCH	TGARCH	TGARCH	TGARCH	GJRGARCH	TGARCH	EGARCH	EGARCH	GJRGARCH
GARCH	2,1	2,1	2,1	1,2	1,2	1,1	1,1	1,1	2,1	1,1	1,1	1,1
ω	0.0003	0.0003	0.0004	0.0004	0.0002	0.0003	0.0004	0.0000	0.0002	-0.0822	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1227)	(0.0000)	(0.0000)	(0.2513)	(0.3649)
α_1	0.0851	0.0822	0.0645	0.0916	0.1063	0.0875	0.0896	0.0147	0.0406	-0.1094	0.0538	0.0416
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0003)
α_2	0.0524	0.0696	0.0640						0.0837			
	(0.0000)	(0.0000)	(0.0000)						(0.0000)			
β_1	0.8636	0.8559	0.8505	0.2880	0.5295	0.9129	0.8977	0.9313	0.8998	0.9909	0.8833	0.9081
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_2				0.6140	0.3746							
				(0.0000)	(0.0000)							
γ_1	1.0000		1.0000	0.7647	0.4830	0.8732	1.0000	0.0927	1.0000	0.0707	0.0924	0.0950
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_2	-0.4004		-0.0749						-0.4992			
	(0.0008)		(0.6105)						(0.0000)			
AIC	**-6.6987**	**-6.6006**	**-6.2994**	**-5.9865**	**-6.2807**	**-5.8651**	**-6.3040**	**-6.7625**	**-6.2885**	**-6.5245**	**-7.4520**	**-6.5113**

The asymmetric coefficient is statistically significant and positive ($\gamma_l > 0$). First, tt confirms that the asymmetric effect by Black (1978) or the different influence between bad news and good news on the stock return volatility. Next, the positive sign means that the shock in the current period is positively influenced by the shock the in the previous period. The majority of the stock markets have lower orders (l=1,k=1), means the shock(l) and volatility (k) from the prior period directly affected shock in the next period (t+1). The shock in the US (INDU, SPX, and CCMP) and India (SENSEX) still persist in the two day period (l=t+2). While, the volatility in in Hong Kong (HSI) and Indonesia (JCI) stock markets will last in the two periods after (k=t+2). These findings imply that stakeholders in Indonesia stock market need to put more attention to the consecutive prior two days stock return volatility before making the current stock market decision.

4.2. Spillover Effect toward Indonesia Stock Market

4.2.1. Cross-Correlation Analysis

Table 3.

The Cross-Correlation

Country	Stock Index	i	Lead[a]	Lag[b]	i	Lead[a]	Lag[b]
US	INDU	0	0.716	0.716	1	**0.721**	0.705
	SPX	0	0.724	0.724	1	**0.729**	0.715
	SPX (-1)	0	**0.729**	**0.729**	1	0.725	0.725
	CCMP	0	0.691	0.691	1	**0.694**	0.681
Hong Kong	HSI	0	**0.832**	**0.832**	1	0.821	0.827
Japan	NKY	0	**0.703**	**0.703**	1	0.694	0.693
	TPX	0	**0.696**	**0.696**	1	0.690	0.685
Singapore	STI	0	**0.838**	**0.838**	1	0.831	0.832
India	SENSEX	0	**0.804**	**0.804**	1	0.799	0.801
Korea	KOSPI	0	**0.774**	**0.774**	1	0.765	0.770
Malaysia	FBMKLCI	0	**0.682**	**0.682**	1	0.676	0.670
Thailand	SET	0	**0.828**	**0.828**	1	0.820	0.822

Notes: [a] JCI, Stock Index (-i); [b] JCI, Stock Index (+*i*)
Bold entries are the highest correlation value

Table 3. displays the results of the cross-correlation between Indonesian volatility stock returns and other volatility stock returns. The results show that in the US stock markets, the highest coefficients are from the correlation between the US stock market volatility (i=0) as a leading indicator with the Indonesian stock market (i=1), INDU (0.721), SPX (0.729), and CCMP (0.694). Since the results can be caused by the impact of the time transaction differences, we then compare the S&P index (t-1) with the Indonesia stock return volatility. It confirmed that the highest coefficient is at i=0, lead[a] and lead[b] with the same value of 0,729, this means that without the time

difference, the S&P index volatility is a coincident index of Indonesia stock return volatility, same like the others Asian stock market volatility.

The coincidence volatility of the Asian stock markets with Indonesia stock market also means that investors in the Indonesia and Asian stock markets have a same day synchronize movement to a certain information. This possibly due to the common investors (Janakiraman & Lamba, 1998) or the investors herding behavior in Indonesia stock market (Koesrindartoto et al., 2020).

The results also show the correlation coefficient with the Singapore and Hong Kong stock markets have the highest value compare to the others (Sari et al., 2017). After the two more mature stock markets, Indonesia stock return volatility has strong correlation with the stock volatility in Thailand and India. The strong correlation between stock market volatility in Indonesia and Singapore and Hong Kong, possibly due to the common investor theory (Janakiraman & Lamba, 1998). In addition, Singapore and Hong Kong are also two of the world bigest financial hub and geographically close to Indonesia. the foreign investment managers in Indonesia usually have a affiliation in a bigger stock market Singapore and Hong Kong.

On the other side, the stock market in Thailand relatively has the same size with its peer in Indonesia, therefore the strong correlation with the Thailand stock market need to be further elaborate, does the stock market in Thailand tend to be more a reference stock market like the stock markets in Singapore and Hong Kong, or is it more like investors alternative stock market of Indonesia stock market?

4.2.2. Vector Autoregressive (VAR) Analysis

The input variables used in the VAR analysis are the 12 stock return volatility. First, the ADF test show that all the stock return volatility data stationer at the 1% level. Next, of the test for all series of volatility stock returns shows that all series rejects the hypothesis of non-stationarity of variables at the 1% level. Next, we use Schwarz Criterion (SC) to determine the optimal lag of the VAR model.

Figure 1. presents the impulse response analysis of Indonesia's stock return volatilityfrom a shock in a particular stock market. In line with the cross-correlation findings, a shock from the US will be transmitted to Indonesia stock market the next trading day, while a shock the Asian stock markets transmit instantly on the same trading day to Indonesia. The shock from the Asian stock markets have bigger a magnitude to Indonesia stock return volatility compared to a shock from the US stock markets. This confirms Lee Miyakoshi (2003) and Lee (2009) who found evidence of the strong spillover effects among the Asian Stock markets. In line with Sari et al. (2017), the magnitude from Singapore and Hong Kong stock markets have the biggest impact to Indonesia.

However, we also found while the shock from Thailand also has significant impact to Indonesia, it has more persistence impact to Indonesia as well. While researchers tend to focus on the study of the association between Indonesia stock market volatility with stock marketvolatility in Singapore or Malaysia (e.g. Saadah, 2013; Lai & Windawati, 2017), this research could be a pacemaker of a further research that focus on the association between Indonesia and Thailand stock markets.

Figure 1.
Impulse Response of Indonesia's Volatility Stock Return
From Shock in a Particular Market

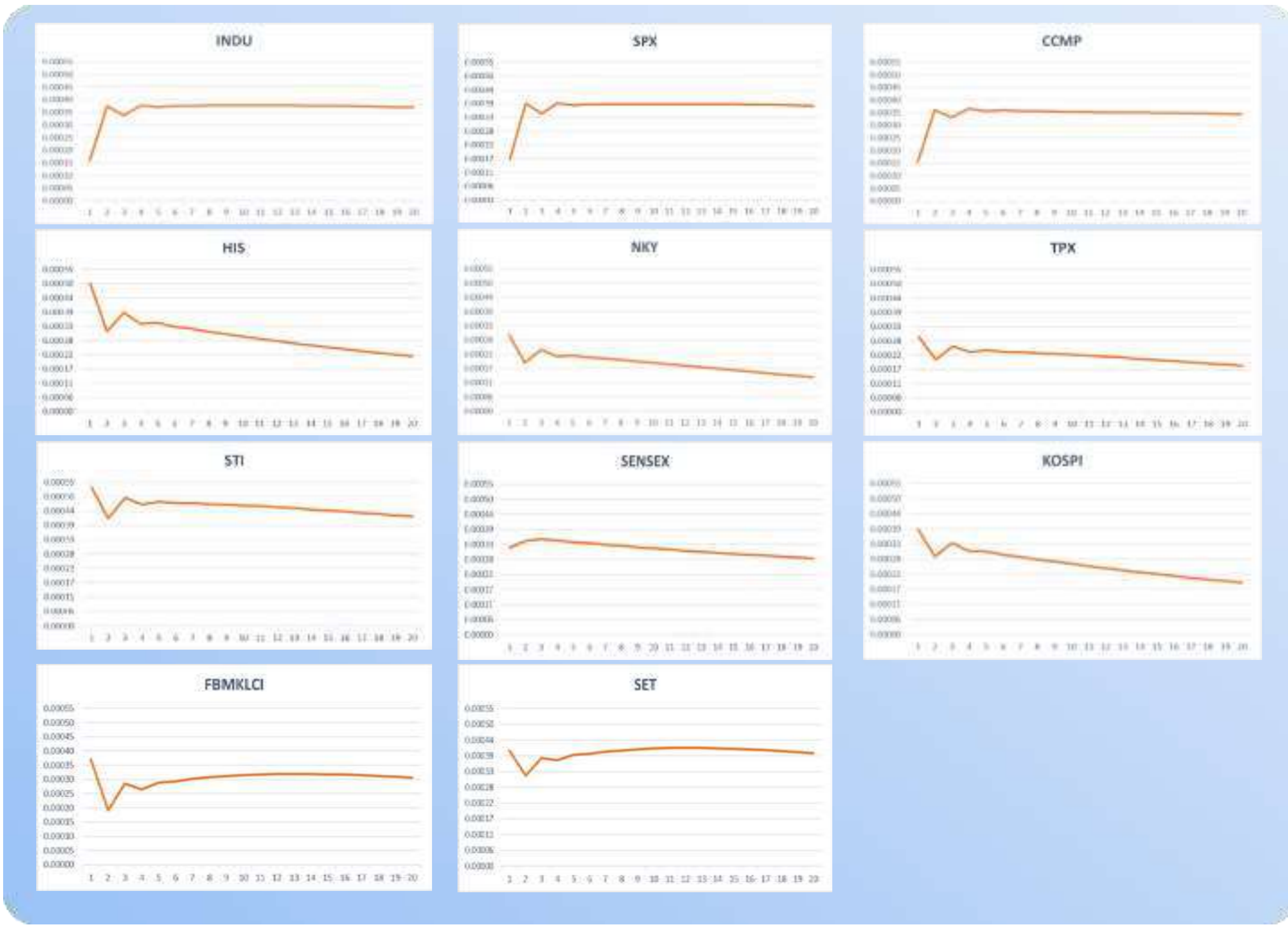

Table 4.

Decomposition of Variance (%) Volatility Return from a Particular Stock Market of Indonesian Stock Market

Country	United States			Japan		Hong Kong	Singapore	India	Korea	Malaysia	Thailand
t	INDU	SPX	CCMP	NKY	TPX	HSI	STI	SENSEX	KOSPI	FBMKLCI	SET
1	1.8473	0.0000	0.0000	0.0000	0.0000	16.3767	0.0000	1.5260	0.0000	0.0000	0.0000
2	8.1415	0.1229	0.0957	0.0510	0.1201	14.1226	0.1592	2.9629	0.0168	0.1351	0.0587
5	12.8237	0.1012	0.1774	0.0458	0.3444	12.6070	0.5457	3.7665	0.0226	0.0860	0.3054
10	16.6474	0.1098	0.1631	0.0457	0.8507	11.1962	1.2832	4.2554	0.0166	0.4508	1.0686
15	18.9958	0.1212	0.1451	0.0538	1.4415	10.1364	2.0891	4.5227	0.0124	1.0839	1.9228
20	20.7615	0.1291	0.1419	0.0739	2.0417	9.2521	2.8910	4.7227	0.0121	1.7331	2.6841

Table 4. shows the forecast error decomposition variance provides an analysis of the contribution of volatility from certain stock markets to the variance of Indonesian stock return volatility. In the table we have excluded Indonesia since the volatility in Indonesia stock market Indonesia is automatically the main source of its variation. Hong Kong stock return volatility has the highest contributor of Indonesian stock return volatility. Again, this confirms the cross-correlation and IRF results.

In addition to the cross-correlation and the VAR models, we also use the Granger Causality test to robust our results. Table 5. presents the results of the bivariate Granger Causality analysis. Consistent with the cross-correlation modes, the stock return volatility in the US markets have the biggest impact to the stock return in Indonesia stock market. However, using the SPX (-1), the coefficient decreases significantly from 98,30 (SPX) to 8,20 (SPX-1), thus this also supports the time differences reason. Following the US markets, the India market stock market also has higher Granger causality coefficient value. Nevertheless, since India stock market closed several hours after Indonesia stock market, this could also because the time difference reason.

After the US and India stock markets, the strong influence of stock market volatility in Singapore and Thailand in line with our result using the cross-correlation and the VAR models. The strong influence of the stock return volatility in the Singapore could be caused by the common investor reason (Janakiraman & Lamba, 1998). Again, further study about the association between the stock market volatility in Indonesia with stock market volatility in Thailand need to be done, to answer the question, does the stock market in Thailand is a reference stock market of the Indonesia stock market, or the alternative stock market for foreign investors in Indonesia stock market.

Table 5.

Bivariate-Granger Causality Test

Country		US				Japan		Hong Kong	Indonesia	Singapore	India	Korea	Malaysia	Thailand
		INDU	SPX	SPX(-1)	CCMP	NKY	TPX	HSI	JCI	STI	SENSEX	KOSPI	FBMKLCI	SET
		does Granger Cause												
US	INDU		2.36	**6.24**	**3.90**	0.38	0.61	**3.99**	**8.23**	**17.43**	**4.73**	**3.83**	1.74	**8.24**
	SPX	1.22			**6.73**	0.12	0.39	**4.50**	**8.83**	**19.21**	**5.40**	**5.15**	2.40	**7.70**
	SPX(-1)	**26656.00**			**8674.78**	**42.85**	**52.01**	**64.99**	**21.25**	**84.78**	**86.16**	**62.58**	**12.63**	**44.09**
	CCMP	**6.32**	**3.24**	**75.67**		**4.01**	**3.14**	**8.53**	**5.02**	**16.57**	**6.85**	**7.79**	**4.37**	**8.29**
Hong Kong	HSI	**265.66**	**276.54**	**8.66**	**235.26**	1.96	**3.05**		**4.34**	**60.26**	**47.15**	**15.52**	**7.42**	**12.37**
Indonesia	JCI	**92.46**	**98.30**	**8.20**	**81.84**	**3.85**	**6.57**	**4.62**		**19.17**	**33.53**	**7.52**	**9.39**	**11.85**
Japan	NKY	**417.35**	**433.22**	**6.01**	**332.84**		**7.05**	**6.61**	**4.35**	**29.76**	**34.10**	**7.81**	**4.08**	**12.01**
	TPX	**369.58**	**381.95**	**4.74**	**297.41**	**3.54**		**7.40**	**3.61**	**31.80**	**33.77**	**6.75**	**5.27**	**8.39**
Singapore	STI	**162.96**	**176.34**	**19.99**	**152.16**	**0.18**	1.14	2.44	1.52		**7.72**	0.56	2.43	1.49
India	SENSEX	**61.78**	**64.88**	**7.36**	**58.99**	**4.19**	**5.70**	**7.11**	**7.08**	**30.52**		**10.78**	**8.24**	**7.98**
Korea	KOSPI	**271.44**	**287.38**	**13.58**	**244.84**	**8.84**	**6.41**	**5.74**	**3.14**	**23.45**	**30.21**		1.98	**12.56**
Malaysia	FBMKLCI	**57.94**	**51.74**	**9.99**	**35.84**	**4.64**	**7.56**	**14.06**	2.88	**17.88**	**28.29**	**8.72**		**6.37**
Thailand	SET	**38.87**	**42.00**	**12.86**	**33.23**	2.83	**4.64**	1.27	**6.73**	**12.91**	**28.67**	**19.90**	2.12	

Bold entries are statistically significant at least at 5-percent level.

4.3. Volatility around Announcement Days

Using the Ordinary Least Square *as* the estimator for the equation (13), table 6. shows that there is no statistical differences of Indonesia stock return volatility around the day of the Bank Indonesia policy rate, inflation and GDP growth announcements. The results give additional evidences that the external spillover effect from the other stock markets have a significant impact to Indonesia stock return volatility. Next, it also implies that the information in the regular Bank Indonesia policy rate, inflation and GDP announcements already incorporated into the stock price. Another possible reason is when the authorities and investors still focus on the end of day data, the macroeconomic indicator announcements may impact the stock market in the intraday movement (Haryadi et al., 2014).

Table 6.

Stock Return Volatility Around the Announcement Day

Coefficient	Announcements		
	BI Policy Rate	Inflation	GDP Growth
ω_0	0.0110 (22.6936)	0.0111 (21.9997)	0.0109 (13.0306)
ω_1 (t-3)	0.0005 (0.7270)	0.0003 (0.4224)	0.0001 (0.0492)
ω_2 (t-2)	0.0004 (0.6037)	0.0003 (0.3808)	0.0000 (0.0001)
ω_3 (t-1)	0.0005 (0.7713)	0.0001 (0.1012)	0.0003 (0.2793)
ω_4 (t+1)	0.0005 (0.7947)	0.0002 (0.3429)	0.0002 (0.2073)
ω_5 (t+2)	0.0005 (0.7881)	0.0001 (0.2031)	0.0002 (0.1480)
ω_6 (t+3)	0.0006 (0.8740)	0.0004 (0.5766)	0.0002 (0.1634)
F-statistics	0.1797	0.0793	0.0231

Note: *T-statics* are shown in parenthesis

IV. Concluding Remark

This paper provides comprehensive assessments of stock return volatility spillover toward Indonesia stock return volatility. Using the best GARCH model to capture daily stock return volatility, as well as the symmetric and asymmetric effects of 12 stock markets, we found that in addition to the spillovers effect from Singapore and Hong Kong (Sari et al., 2017), Thailand stock return volatility has bigger and persistence impact of the Indonesia stock return volatility. These need to be further elaborate, why an Indonesia peer countries has a relatively bigger influence to Indonesia stock return volatility. Furthermore, this paper also finds that around the domestic macroeconomic indicator announcement dates there is no significant increase of stock return volatility.

The findings of this paper implied some recommendations to stock stakeholders, including investors as well as the stock market authority. First, the continuous effort to enhance domestic retail investor participation in emerging stock market, including in Indonesia is a must (Koesrindartoto et al., 2020), in regard to minimize the spillovers effect from the other stock markets that relatively have more impact to the institutional and foreign investors. Next, diversification of the foreign investors in the Indonesia stock market could be an additional alternative, especially foreign investors from other than Singapore and Hong Kong. Furthermore, in addition to the current foreign stock market surveillance, stakeholders need to enhance surveillance to the Thailand stock market volatility, since it has strong and persistence influence in Indonesia stock market. Finally, due to the reason that on the daily stock return volatility, this paper cannot find significant evidence that domestic macroeconomic indicators, Bank Indonesia policy rate, Inflation and GDP growth announcements impact stock market volatility around the announcement dates, stock market stakeholders need to put extra attention to the irregular information that potentially bring negative sentiments to the market.

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