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THE RISK OF SUB-PRIME MORTGAGE CRISIS AND COVID-19 PANDEMIC: LESSON LEARNED FROM INDONESIA

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Abstract: This study aims to analyze the risks in Indonesia's financial sector related to the sub-prime mortgage case in the United States and COVID-19 pandemic. This study uses a comparative analysis of the time series model from 2006 to 2020. The data includes stock index, exchange rate, and interest rate variables collected from Datastream. This study calculates the mean level of the model and the variance level of the model, namely ARMA, GARCH, and EGARCH. The results of this study are, in the three years before the sub-prime crisis, no autocorrelation for all variables, whereas the sub-prime crisis period showed the existence of autocorrelation. However, there is no autocorrelation during the COVID-19 pandemic. The stock index variable's optimal model is the GARCH model, while the exchange rate and interest rate use the EGARCH model. Furthermore, the financial sector's risk increased during the subprime mortgage crisis as indicated by an increase in stock index volatility, exchange rate, and interest rate from the pre-crisis period.

Keywords: risk, ARMA, GARCH, EGARCH, sub-prime crisis, COVID-19

Abstrak: *Penelitian ini bertujuan menganalisis risiko di sektor keuangan Indonesia terkait kasus subprime mortgage di Amerika Serikat dan pandemi COVID-19. Penelitian ini menggunakan analisis komparatif model time series dari tahun 2006 hingga 2020. Data penelitian meliputi variabel indeks saham, nilai tukar, dan suku bunga yang bersumber dari Datastream. Penelitian ini menghitung mean level model dan level varians model yaitu ARMA, GARCH, dan EGARCH. Hasil penelitian ini adalah, pada tiga tahun sebelum krisis subprime tidak terjadi autokorelasi untuk semua variabel, sedangkan pada periode krisis subprime menunjukkan adanya autokorelasi. Namun, tidak ada autokorelasi selama pandemi COVID-19. Model optimal variabel indeks saham adalah model GARCH, sedangkan nilai tukar dan suku bunga menggunakan model EGARCH. Selain itu, risiko sektor keuangan meningkat selama krisis subprime mortgage yang ditunjukkan dengan peningkatan volatilitas indeks saham, nilai tukar, dan suku bunga dari periode sebelum krisis.*

Kata kunci: *risiko, ARMA, GARCH, EGARCH, krisis sub-prime, COVID-19*

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INTRODUCTION

The world has been shocked by the sub-prime mortgage financial crisis in 2008-2009 in the United States. At the end of 2019, the world was again shocked by the pandemic that led to financial difficulties for many countries. Both cases are different, as the COVID-19 crisis concerning health status. However, the economy is going down as they affect the financial system.

In the case of the sub-prime mortgage, a peak of housing prices in 2005 and its significant decline led to bankruptcy in the mortgage industry. It resulted in large losses at many financial institutions whose business was related to housing loan securitization in the United States. It included big corporations, such as Lehman Brothers. , Merrill Lynch, HSBC finance corporation, Fannie Mae, and Freddie Mac, as banks mostly could not roll over their borrowing and put them in major trouble (Blinder, 2013). This loss forced the United States government to rescue several financial institutions as one of the largest bailouts in history and reform its economic policies.

There are similarities between these two crises (sub-prime mortgage and COVID-19). The financial vulnerability has appeared and the adverse economic shock. The uncertainty now remains very high as the world has not been invented the potent vaccine yet. With months and months of quarantine to flatten the spread of the virus, it affects economic activity. This health crisis also creates a contagion risk as it happened in the financial crisis.

Similarly, the importance of liquidity and the issuance of debt are concerned. Transmission sources from the Global Financial Crisis (GFC) could spread from many channels. In the Indonesian economy, the channels are the stock market, banking, capital market, and real sector (Murniningtyas, 2009). Other plausible transmission channels are investments (including portfolios and foreign direct investment) and exports that occur in international trade, both of which will affect Gross Domestic Product (GDP) and inflation (Anwar and Nguyen, 2018). This transmission also occurs in the recent pandemic era.

The crisis transmission speed to a country varies depending on the countries' level of linkages (for a financial crisis like sub-prime mortgages). Moreover, the health crisis affects all countries without exception. Indonesia's economy is open for foreign channels, especially in the financial sector, including the Jakarta Composite Index, the exchange rate, and interest rates. Regarding the most recent crisis, the Coronavirus also significantly impacts stock market reaction compared to previous health pandemics (Baker et al. 2020). The social distancing leads to low sending and low credits, but high in non-performing loans that impact the economy's various sectors.

Risk is an essential factor when studying financial crises. It refers to the uncertainty of an event's consequences or unfavorable events that may occur in the future. In this study, volatility is one of the risk indicators. Each indicator's volatility measures the variation or spreads against the average over a certain period. Several measuring volatility methods, such as ARCH, GARCH, switching models, bilinear models, and Value at Risk, are mostly used. . Measuring volatility in the financial sector is very important because it reflects a country's economic condition and stability. Therefore, this study covers the measurement of financial sector risk with the GARCH model related to external factors by taking sub-prime mortgage and COVID-19 pandemic cases.

This study aims to provide an overview of the risk or stability of the financial sector in Indonesia. The originality of this study comes concerning subprime mortgage case in the United States and the on-going COVID-19 pandemic using the GARCH model, with a focus of research: (1) to compare the presence or absence of autocorrelation in the movement of stock indexes, exchange rates, and interest rates in the period before and after the sub-prime crisis; and (2) to compare stock index volatility, exchange rates, and interest rates in the periods before and after these two crises.

Understanding volatility during a crisis can benefit regulators, investors, and company management. Regulators can obtain information to be used in formulating various policies both for preventive and repressive measures. Likewise, investors and company management can analyze the effects of a crisis on the portfolio and the company's performance. Hence they can make quick and appropriate decisions to adjust to the crisis conditions.

METHODS

This study uses secondary data in the form of the daily time-series data for each financial risk indicator (stock index, exchange rate, and interest rate) with a sample of a single country, Indonesia, from January 2006 to November 2020. The data are downloaded from Datastream. It includes a comparative analysis of the mean level of the model and the model's variance level.

This study hypothesizes that volatility is increased during both crises. It is based on premises that the uncertainty is higher, and the assets are compensated with higher returns for bearing higher levels of risk (Schwert, 1989). According to previous studies, the sensitivity of time-series yields of stocks, interest rates, and exchange rates with the GARCH in Mean (GARCH-M) model (e.g., Ryan and Worthington, 2004; Elyasiani and Mansur, 1998; Sah, 2011).

To measure financial sector risk, stock index, exchange rate, and interest rate data are used. The stock index used is the Jakarta Composite Index (JKSE), representing an indicator of capital market movements. The exchange rate (EXCH) uses the exchange rate of the rupiah (IDR) to the United States dollar (USD) with the consideration that US Dollar is the most actively traded currency and is the most widely used in financial records. While the interest rate uses the 90-day SBI interest rate and Bank Indonesia daily repo rate data, the data is the closest data to bond yield data, considered more representative.

The data are analyzed as follows: At the mean level, the most optimal model will be used between the Autoregressive Process (AR) model, the Moving Average Process (MA) model, or the ARMA model (1.1). The selection of optimal models uses the indicators Log-Likelihood (LL), Akaike Info Criterion (AIC), and Schwarz Criterion (SC). The framework of this study in Figure 1 with these criteria, the following model will be obtained:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots + \phi_p y_{t-p} + u_t$$

$$y_t = \mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \ldots\ldots + \theta_q u_{t-q}$$

$$y_t = \mu + \phi y_{t-1} + \theta u_{t-1} + u_t$$

where, $u_t \sim N(0,\sigma^2_t)$

While at the variance level, the Generalized Autoregressive Conditionally Heteroscedastic (GARCH (1.1) model follows:

$$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \beta \sigma^2_{t-1}$$

The GARCH model (1.1) above must meet two requirements, namely (1) α and β must be greater than zero or positive, and (2) $\alpha_1 + \beta$ must be less than or equal to 1. If these two things are not fulfilled, an Exponential GARCH (EGARCH) model will be used, accommodating non-negativity constraints and leverage effects. The variance equation, according to The EGARCH model, is:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}} \right]$$

Refer to Siregar et al. (2012), the financial crisis began on 15 September 2008 at the time of the announcement of the Lehman Brothers bankruptcy, so that the time limit for examining before and after the subprime mortgage crisis began on that date. Whereas the period of measuring volatility is used for two years, longer than the crisis period based on Sah (2011) research in India is up to 31 March 2010. Therefore, the period pre-mortgage crisis began on 15 September 2006 to 14 September 2008, and the period after the crisis began on 15 September 2008 to 15 September 2010. Meanwhile, the on-going crisis period begins from 11 March 2020 until the latest data this study can collect (1 November 2020). This period has been taken as the World Health Organization (WHO) announces Coronavirus's pandemic status.

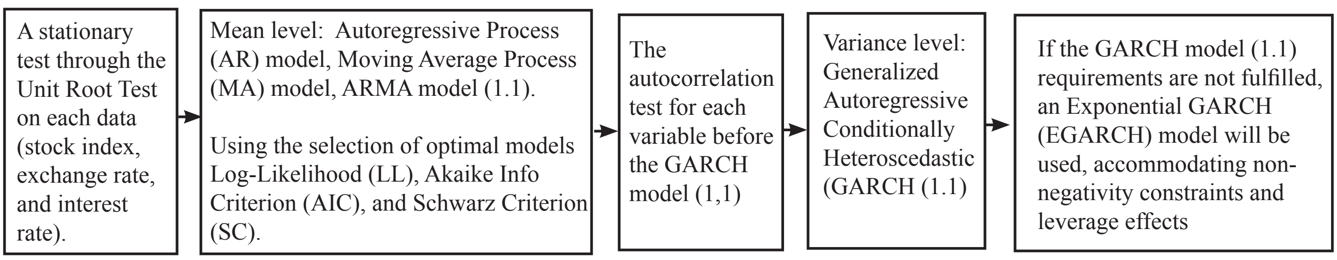

Figure 1. Research framework

RESULTS

At the beginning of the data processing, a stationary test was carried out through the Unit Root Test on each data (stock index, exchange rate, and interest rate). The data becomes stationary after one differencing. The 90-day SBI daily interest rate is calculated by continuous compounding, following Ryan and Worthington (2004). JKSE return data, USD/IDR return, and movement of SBI interest rates are then mapped in Figures 1 to 3.

From the three Figures, it can be seen that there is volatility clustering as often occurs in time series data, namely the tendency of high volatility. In addition to showing the presence of volatility clustering, from the six figures, it can be seen that there was an increase in volatility during the sub-prime crisis (2008-2009), especially in the JKSE and EXCH. While interest rates increased relatively high at the beginning of the crisis, this was the central bank's response to the crisis. During the health pandemic, the first quarter of 2020 experienced high volatility in JKSE and EXCH variables. However, during the COVID-19 pandemic, the interest rate is low due to high liquidity and government response to lower credit costs. The trend of this interest rate is down warding.

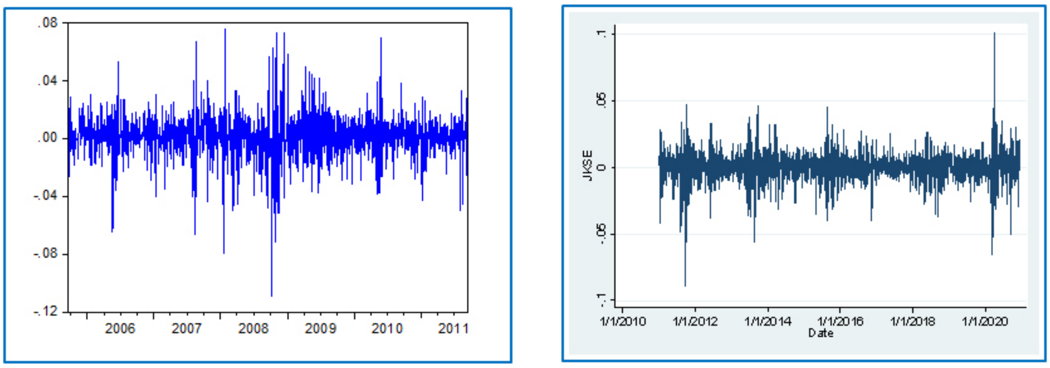

Figure 1. JKSE

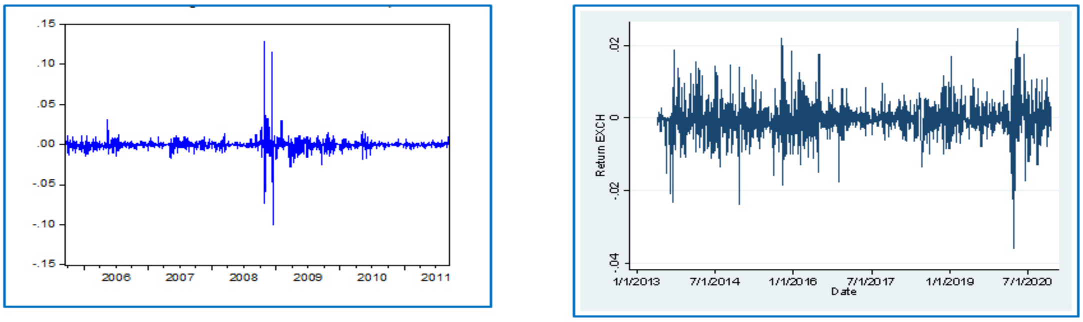

Figure 2. Exchange Rate USD to IDR

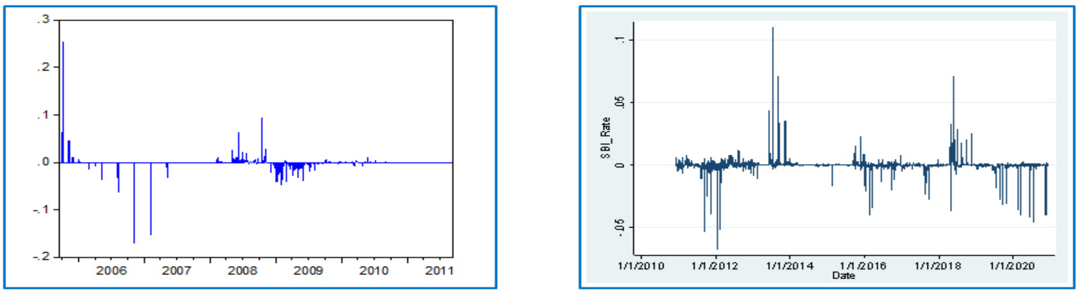

Figure 3. SBI Interest Rate

Furthermore, as shown in Descriptive Statistics in Table 1, the standard deviations for the JKSE, EXCH, and SBI are 0.019, 0.006, and 0.008, respectively, for all crises period. The mean for all variables is close to zero. From these data, it can be concluded that JKSE is more fluctuating than EXCH and SBI. Furthermore, by looking at the value of skewness, the data distribution is not symmetrical, especially on the JKSE is sloping to the left (skewness = -0.487), while EXCH and SBI are sloping to the right (skewness = 2.182 and 4.611). Besides, kurtosis of all data values above 3 (three) reflects that the data distribution is leptokurtic, so it is not sufficiently explained by the linear model and more precisely uses the GARCH model.

Before the GARCH model (1,1) is applied, the autocorrelation test for each variable is tested for each observation period. The result is JKSE, EXCH, and SBI variables have no autocorrelation (white noise) in the period before the crisis. Hence, it is directly calculated with the GARCH model without going through ARMA modeling. While after the crisis, all variables contain autocorrelation so that the modeling is carried out at the mean level (ARMA) before modeling GARCH. According to Sah (2011), which states that the GARCH model is considered optimal in measuring time series data that has volatility clustering and is in the form of leptokurtosis distribution, then the GARCH model will be used as long as there are no asymmetric and leverage effects shown by positive α_1 and β and $\alpha_1+\beta \leq 1$. If one of the two GARCH model criteria is not met, then the EGARCH model will be used. From the results of calculations, the JKSE model is optimal by using the GARCH model, while EXCH and SBI are optimal using the EGARCH model.

A comparison of JKSE volatility is shown in Table 2 and 3. At the mean level, autocorrelation occurs in the crisis period that forms the MA model (11, 16, 17, 26, 28), meaning that the index on t-day is affected by errors from t-11, t -16, t-17, t-26, and t-28. This may be caused by the presence of information or policies that affect the index, so the market becomes inefficient in times of crisis (weak form). Likewise, in terms of risk, the index during a crisis shows higher volatility compared to the pre-crisis period, which is indicated by the value of $\alpha_1 + \beta = 0.973247$ ($\alpha_1 + \beta$ before the crisis = 0.865973). The calculation results are statistically significant at the 5% level. During COVID-19, as shown in Table 4, the autocorrelation did not occur as the index is still in uncertainty and not affected by the errors from the previous period.

GARCH (1,1) for SBI yields negative α_1 and for EXCH produces $\alpha_1 + \beta > 1$, so the Exponential GARCH (EGARCH) model is used as presented in Table 5 to 10 for EXCH and SBI variables. This result contradicts a finding in Karmakar (2005), which shows that the GARCH (1,1) model provides good forecasts of volatility.

Table 1. Descriptive Statistics (all period)

Statistic	JKSE	EXCH	SBI
Mean	0.0009	-0.00007	-0.00019
Standard Deviation	0.019	0.006	0.008
Skewness	-0.487	2.182	4.611
Kurtosis	8.55	102.1	270.9

Table 2. GARCH (1,1) JKSE before the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	0.001565	2.549462	0.0108
Variance Equation			
α0	0.0000326	4.310527	0.0000
α1	0.247301	5.925482	0.0000
β	0.618672	11.21491	0.0000

Table 3. GARCH (1,1) JKSE after the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	0.001786	2.494096	0.0126
$\theta(11)$	-0.108956	-2.852961	0.0043
$\theta(16)$	-0.147692	-3.135838	0.0017
$\theta(17)$	0.125159	2.690150	0.0071
$\theta(26)$	0.138186	3.297125	0.0010
$\theta(28)$	0.110828	2.522854	0.0116
Variance Equation			
α_0	0.00000532	4.280158	0.0000
α_1	0.059243	5.734863	0.0000
β	0.914004	86.01267	0.0000

Table 4. GARCH (1,1) JKSE during COVID-19 pandemic

Variables	Coefficients	Z-statistic	Prob
μ	0.003887	-1.78	0.0560
α_0	0.007664	0.18	0.8064
α_1	0.094431	1.98	0.2889
B	0.766810	1.32	0.2119

Table 5. EGARCH (1,1) EXCH before the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	-0.000160	-1.233542	0.2174
Variance Equation			
ω	-2.364182	-6.722166	0.0000
β	0.418516	8.888247	0.0000
γ	0.016189	0.459344	0.6460
α	0.817781	28.08839	0.0000

Table 6. EGARCH (1,1) EXCH after the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	-0.000435	-4.542713	0.0000
$\theta(1)$	-0.104884	-3.387744	0.0007
θ (30)	-0.174481	-13.48932	0.0000
$\theta(31)$	-0.079666	-5.831804	0.0000
$\theta(33)$	-0.205214	-9.418186	0.0000
Variance Equation			
ω	-2.027974	-9.113276	0.0000
β	0.717154	20.55283	0.0000
γ	0.052868	1.947252	0.0515
α	0.847106	38.79111	0.0000

Table 7. EGARCH (1,1) EXCH during COVID-19 pandemic

Variables	Coefficients	Z-statistic	Prob
μ	-0.0055	-1.908	0.0662
ω	-1.0988	-1.231	0.5310
β	0.5677	0.897	0.9132
γ	0.0071	0.091	0.2998
α	0.5442	0.988	0.0910

Table 8. EGARCH (1,1) SBI before the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	-0.000000281	-1.890299	0.0587
Variance Equation			
ω	-5.151404	-19.06386	0.0000
β	-2.368283	-18.51173	0.0000
γ	-0.981049	-13.94896	0.0000
α	0.437161	14.82407	0.0000

Table 9. EGARCH (1,1) SBI after the crisis

Mean Equation			
Variables	Coefficients	Z-statistic	Prob
μ	-0.000295	-9.177237	0.0000
θ(5)	0.087306	14.65802	0.0000
θ(10)	0.173509	12.60551	0.0000
θ(16)	0.050269	38.24298	0.0000
θ(20)	0.139518	15.56023	0.0000
θ(25)	0.071872	7.364150	0.0000
θ(30)	0.241707	21.34334	0.0000
θ(35)	0.027779	11.42151	0.0000
θ(36)	-0.099747	-10.93124	0.0000
Variance Equation			
ω	-5.597674	-27.46013	0.0000
β	-0.866231	-17.93577	0.0000
γ	-0.411573	-9.129047	0.0000
α	0.458648	23.67047	0.0000

Table 10. EGARCH (1,1) SBI during COVID-19 pandemic

Variabels	Coefficients	Z-statistic	Prob
μ	-0.0001211	-1.87	0.0665
ω	0.0067644	1.07	0.1920
β	-1.10133	-1.20	0.0930
γ	-0.30221	-0.2655	0.2390
α	0.53220	1.773	0.3112

From the four tables (Table 1-4), it can be concluded that the sub-prime crisis caused autocorrelation on the EXCH and SBI variables, each of which was shown by the MA model (1, 30, 31, 33) and the MA model (5, 10, 16, 20, 25, 30, 35, 36). In contrast, the COVID-19 has not caused autocorrelation in these variables. In the period before the sub-prime crisis, these two variables were white noise. This reflects information that affects EXCH and SBI interest rates, including policies and interventions from the Central Bank to reduce the crisis's adverse effects.

The EGARCH model calculation for the EXCH variable is statistically insignificant at the 5% level, both in the period before and after the crisis. The exchange rate volatility during a crisis is higher than the pre-crisis period as reflected by the value of $\beta + \alpha_1 = 1.56426$ ($\beta + \alpha_1$ before crisis = 1.236297). This is in line with Sah (2011), which indicates high volatility during the sub-prime mortgage crisis period. Similar to the calculation of EXCH variables, the EGARCH model for SBI variables shows that SBI volatility during crises is higher than the pre-crisis period reflected by the value of $\beta + \gamma + \alpha_1 = -0.819156$ ($\beta + \gamma + \alpha_1$ before crisis = -2.912171).

In general, the results of this study indicate an increase in volatility in the JKSE, EXCH, and SBI interest rates in case of a sub-prime mortgage crisis, relatively similar to the research of Siregar et al. (2012), which concluded the JKSE volatility, exchange rate, and inflation in the short term. They also concluded that the domestic economic fundamentals (GDP, Inflation, money market, and capital market) were quite strong, and the effectiveness of fiscal and monetary policies could control the impact of the crisis in the short term, such as low-interest rates, reducing unemployment, monetary policy easing, government spending, low-taxation, and transfer payments. The results also support Charfeddine and Ajmi (2013) that volatility is not spuriously created but linked to other events in the crisis period. However, we do not find any autocorrelation during the COVID-19 pandemic yet.

Managerial Implications

During the sub-prime mortgage crisis, the financial downturn in the United States affects countries that have linked their economic transaction directly or indirectly. Even though there is no evidence that the autocorrelation exists during the COVID-19 pandemic, it may happen in the coronavirus COVID-19 pandemic later. As evidenced by volatility in the stock market, forex market, and interest, the Indonesian economy began to fluctuate. This study recommends that the policymakers and stakeholders mitigate the economic damage caused by the financial risk for national scope and corporates and households. In addition, the results have some implications for the financial regulator to formulate various policies during crisis periods.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

From the description and explanation in the previous section, the following conclusions can be drawn: (1) JKSE return movements, EXCH (USD / IDR exchange rates), and 90-day SBI interest rates follow a volatility clustering pattern, (2) Descriptive Statistics data show JKSE is more fluctuating compared to EXCH and SBI. All distributions are leptokurtic, so it is more appropriate to use the GARCH model, (3) In the period before the crisis, no autocorrelation was found for all variables, whereas in the crisis period, there was an autocorrelation. However, during the COVID-19 pandemic, there is no autocorrelation found. This shows that there is a variety of information affecting financial market conditions and policy responses in order to control the impact of the crisis, (4) Calculation of the JKSE variable uses the GARCH model. In contrast, EXCH and SBI use the EGARCH model because of the asymmetric and leverage effects, (5) Financial sector risk shows an increase during the subprime mortgage crisis as indicated by the increase in the volatility of the JKSE variable, EXCH, and SBI interest rates from the pre-crisis period. Theoretically, this paper shows the better methodology to calculate the volatility during the crisis periods in each variable used.

Recommendations

Research on the sensitivity of time-series of stocks, interest rates, and exchange rates with the GARCH in Mean (GARCH-M) model has been extensively studied. This study suggests adding more factors such as industry-specific characteristics, firm-specific variables, and government regulation during the crisis period to fill the literature gap for future research. It is also recommended to add more cross countries evidence to compare the financial risk in each country. As volatility is continuous and projections of conditional volatility require time to reach a fixed variance level, adding more time series will be valuable to get more robust results. In addition, a more advanced model of asymmetric GARCH to capture volatility clustering during the pandemic crisis, which not yet over, is left for future research.

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