The Effect of Covid-19 Pandemic on Stock Market Volatility: Tales from Two Sectors

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Abstract. This study investigates the impact of the Covid-19 pandemic on the volatilities of two sectoral indices in Indonesia. The primary objective is to empirically examine the relationship between the occurrence of the pandemic, volatility, and trading volume. The authors employ GARCH modeling to analyze the two measurements, incorporating the Covid-19 variable as an external regressor. Data samples from two distinct sector indices of the Energy and Technology sectors in the Indonesian Stock Exchange are utilized, encompassing the periods before and after the initial Covid-19 case in Indonesia.

1 Introduction

The outbreak of the Covid-19 pandemic in early 2020 has caused a global crisis with significant economic implications. Unlike previous crises, such as the 2008 global financial crisis, which were primarily driven by imbalances and risks in the financial sector, the Covid-19 crisis emerged suddenly and resulted from a viral disease that severely disrupted economic activities worldwide. Scholars have drawn parallels between the current crisis and historical crises, highlighting the unique nature of the Covid-19 crisis in terms of its impact, scope, and underlying causes. These observations have sparked research interest in understanding the factors and responses of countries and firms in dealing with the Covid-19 crisis.

This research study focuses on investigating the impact of the Covid-19 pandemic on stock market volatilities. The authors aim to empirically examine the relationship between the growth of Covid-19 cases and stock prices' reactions. To achieve this, they employ statistical modeling, specifically GARCH modeling, which allows for an analysis of the relationship between the pandemic variable and volatility while considering the effects of other factors. The study utilizes data samples from the Indonesian Stock Exchange, focusing on two different sector indices, and covers the periods before and after the initial Covid-19 case in Indonesia.

The Covid-19 pandemic has had a profound global impact, affecting various sectors and economies worldwide. Lockdown measures and health protocols implemented by authorities have resulted in an economic downturn, with sectors like exports, imports, air travel, and local businesses being particularly hard hit. However, the stock market has exhibited a peculiar "disconnect" from the overall economic situation. Despite the economic challenges, stock markets have shown resilience and even recorded growth in some cases, indicating a long-term outlook by investors who anticipate economic recovery in the future. However, short-term cash flows have declined, suggesting potential long-term declines in stock market performance.

While numerous studies have examined investment strategies and the effects of the Covid-19 pandemic on stock markets, only a limited number of extensive statistical studies have specifically focused on the Indonesian market. Existing studies have predominantly employed qualitative approaches, such as case studies and qualitative analysis of media and government sources. This research aims to bridge the gap by conducting a thorough statistical analysis of the Covid-19 impact on the Indonesian stock market.

The Indonesian stock market exhibits distinct characteristics influenced by the country's unique economy and environment. Investor behavior, both institutional and individual, plays a significant role in shaping the stock market's trends and trading strategies. Since the outbreak of the Covid-19 pandemic, the Indonesian Stock Exchange has experienced a significant decline in the price index, followed by a gradual recovery. However, the index has not yet reached pre-pandemic levels. In contrast, stock markets in countries like the United States, Europe, and Asia have demonstrated stronger growth, driven by sectors such as technology. The disparity in sector performance raises questions about the varying effects of the pandemic across different sectors of the Indonesian economy.

In short, this research aims to provide insights into the impact of the Covid-19 pandemic on stock market volatilities, specifically in the Indonesian context. By employing statistical analysis techniques, the study seeks to examine the relationship between the growth of Covid-19 cases and stock price reactions. The findings will contribute to a better understanding of the dynamics

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between the pandemic and stock market performance, shedding light on the unique characteristics and challenges faced by the Indonesian stock market in the wake of the Covid-19 crisis.

2 Literature review

2.1 Determinants of stock market volatility

Determining factors of stock market volatility have been extensively studied, consistently revealing a correlation between volatility and trading volumes. The current global pandemic has acted as a catalyst for economic disruption, necessitating a deeper understanding of the causes and effects of volatility.

Notably, studies, such as Karpoff (1987), have explored the relationship between stock market volatility and various factors [1]. Karpoff’s study demonstrated a positive relationship between price changes and volumes in the U.S. stock market. This relationship holds significant importance for several reasons. Firstly, it contributes to the understanding of price speculation distribution. Secondly, it enhances comprehension of the financial market structure. Lastly, it provides valuable insights for event studies that involve the interplay between these variables. The findings support a “contemporaneous” relationship between price changes and trading volumes.

Meanwhile, the “Mixture of Distribution Hypothesis” (MDH), introduced by Clark (1973), suggests that stock returns and trading volumes exhibit a positive relationship due to their co-dependence on an underlying common variable, such as the information flow rate [2]. Several studies, including Sabri (2004), have further supported this notion by identifying trading volume as a predictor of return volatility in developing economies. Numerical statistical studies also confirm the positive contemporaneous relationship between returns and trading volumes [3].

Recent studies conducted in the early 2000s by Lee and Rui (2002) and Chen et al. (2001) observed the same conclusions in stock exchanges across different countries [4][5]. Additionally, Chen (2012) found a significant positive relationship between the S&P 500 price index and trading volume before the year 2000 [5].

To explore potential asymmetries in the relationship between returns and volumes, Chen (2012) examined different stock market cycles. This investigation was motivated by the presence of seasonal fluctuations in returns and the recognition that various factors differ between bear and bull markets, such as investor behavior. Chen's study revealed a negative correlation between volume and returns during bear markets, while the opposite held true during bull markets [5]. These findings highlight the importance of considering market conditions when analyzing the relationship between trading volumes and returns.

Another theory, the "Sequential Information Arrival Hypothesis" (SIAH), posits that the positive relationship between price changes and trading volumes stems from the sequential dissemination of information. As new information reaches investors, those with better access react more swiftly, leading to an initial equilibrium. Eventually, all investors respond, resulting in a final equilibrium. Lagged characteristics play a role in understanding volatility and returns, as lagged information on returns relates to current trading volume and vice versa.

Studies by Gallant et al. (1992) and Hiemstra and Jones (1994) examined the correlation between volumes, price changes, and volatility [6] [7]. These studies found a strong direct relationship between return fluctuations and trading volume, as well as between trading volume and volatility.

Furthermore, Pisuttasalasil and Gunasekarage (2007) discovered that returns can predict trading volumes, while volumes have a limited impact on anticipated returns [8]. Quintile regression analysis conducted by Chuang et al. (2009) revealed heterogeneous results for the relationship between volumes and returns across different quintiles [9]. Conversely, an OLS study by Gebka and Wohar (2013) in Pacific Basin countries found no causal relationship between returns and past trading volumes [10].

2.2 The impact of covid-19 pandemic on energy and technology sectors


In contrast, Kusumahadi and Permana (2021) used the Threshold-GARCH model and observed that COVID-19 affected stock return volatility in all countries except the United Kingdom, showing a positive relationship between the presence of COVID-19 and return volatility [12]. Bash (2020) analyzed the effects of COVID-19 on 30 stock indices and found large negative stock market returns [13]. He et al. (2020) investigated the direct effects and spillovers of COVID-19 on stock markets in various regions, revealing short-term negative effects and bidirectional spillovers between American, European, and Asian stock markets [14].

Chaudhary et al. (2020) examined the volatility of stock markets in the top 10 countries and found average negative returns in the first half of 2020, indicating a bearish trend [15]. The energy sector was significantly impacted by COVID-19, as shown by Hasan et al. (2021), who used the SVAR model and found negative effects on the MSCI World Energy Index, MSCI World Index, and Baltic Dry Index due to decreasing power consumption and plummeting oil prices [16]. However, the technology sector demonstrated resistance to the pandemic's adverse impacts, as evidenced by Liew (2021), who found that the Information Technology and Health care sectors outperformed the overall stock market during the pandemic [17]. Additionally, studies have shown a positive relationship between the Indonesian Stock Exchange and international indices, with Robiyanto et al. (2019) revealing a significant positive relationship between the Jakarta Composite...
Index and the Dow Jones Industrial Average, while the USD/IDR exchange rate exhibited a negative relationship with the Jakarta Composite Index [18].

2.3 Hypotheses

Previous studies have established a contemporaneous relationship between returns and volumes, supported by the MDH and SIAH theories. This implies that the effects of the pandemic on the stock market will simultaneously impact both returns and volume. Volatility in the market is commonly associated with uncertainty, and according to Ang and Liu (2007), the market tends to be in a bearish scenario during periods of volatility and uncertainty [19].

Chaudhary et al. (2020) found that all countries experienced a rebound in returns during the second quarter of 2020 [15]. Although the future of the pandemic remains uncertain, stock markets are gradually returning to their pre-COVID-19 state. Examining specific sectoral indices, the energy sector has been significantly affected by the COVID-19 pandemic. Hasan et al. (2021) used the SVAR model and found negative and considerable effects of the pandemic on three stock indices: MSCI World Energy and the Energy Stock Index (IDX). To achieve this, we utilized the GDH and SIAH theories. This implies that the volatility in the market follows international indices, as there is a positive relationship between the Jakarta Composite Index (JCI) and the Dow Jones Industrial Average (DJIA).

Based on the literature reviewed, this study proposes the following hypotheses regarding the impact of the COVID-19 pandemic on return volatility in the Indonesian stock market, specifically in the Energy and Technology sectors:

**H1.** The effects of COVID-19 on return volatility are less pronounced in the Technology Stock Index compared to the Energy Stock Index.

**H2.** The effects of volume on return volatility are more significant in the Technology Stock Index compared to the Energy Stock Index.

3 Methods

3.1 Methodology background

The primary objective of this study is to analyze the behavior of stock returns and volatility during the global financial and Covid-19 induced crises in the Indonesian Stock Exchange (IDX). To achieve this, we utilized the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which has demonstrated its effectiveness in estimating conditional volatility in both developed and emerging markets.

The ARCH (Autoregressive Conditional Heteroskedasticity) model, initially developed by Robert Engle in 1982 and later generalized as GARCH by Tim Bollerslev in 1986, is specifically designed to model conditional variances. These models are widely employed in economic and financial time series analysis, where the variance of the dependent variable is assumed to be dependent on past values of both the dependent and independent variables.

3.2 Data

The dataset used in this study comprises the daily returns of the LQ45, the energy (IDXENERGY) and the technology (IDXTECHNO) indices from the Indonesian Stock Index (IDX). The IDX recently introduced 11 new indexes, replacing the previous JASICA indexes. Due to limited data availability for these two indices, historical prices of all listed companies included in the indices were compiled and calculated based on the prices set by the IDX for each index.

The Energy Index consists of 66 listed companies, while the Technology Index includes 16 listed companies. Daily Covid-19 cases data will be collected from OurWorldInData.org. To assess the impact of Covid-19 in Indonesia, the growth rate will be calculated using the equation "Daily Growth = Log (1-total cases Day T) - Log (1-total cases Day T-1)". The regression period for this study starts from the first reported Covid-19 case in Indonesia on March 2, 2020, and covers the timeframe of March 2, 2020, to April 30, 2021.

3.3 Empirical model

As discussed, this paper uses the GARCH model to examine the impact of COVID-19 on the volatility and volume in the Indonesian stock market. In this regard, we adopt the GARCH (1,1) model for measuring both the impact of Covid-19 in Indonesia and volume on the volatility of the market. For the first part, of measuring the impact of Covid-19, we utilise the model as follow:

\[ h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 COVID_t \]  

(1)

where \( h_t \) shows the conditional variance term in period \( t \), \( \omega \) is the constant offset term in the model. The \( \alpha_1 \) represents the coefficient term for the squared residual for the past period, \( \varepsilon_{t-1}^2 \) represents the squared residual for the past period. \( \beta_1 \) represents the coefficient term for the conditional variance of the past period, while \( h_{t-1} \) represents the conditional variance of the past period. \( \delta_1 \) will be the coefficient term for the daily Covid-19 cases, while \( COVID_t \) will show daily cases calculated at date \( t \).

Meanwhile, for measuring the impact of volume on the volatility, we employ the following GARCH equation:
Model (2) has all the same variables with the Model (1) with the addition of \( \gamma_t V_t \), where \( \gamma_t \) is the coefficient for volume and \( V_t \) represents the current period’s volume traded. This variable will cater for measuring the impact of volume on the volatility.

\[ h_t = \omega + \alpha_t e^2_{t-1} + \beta_1 h_{t-1} + \gamma_t V_t \]  
\( (2) \)

### 4 Results

Estimation results of Equation (1) and Equation (2) for IDXEnergy and IDXTechno are presented in Table 1 and Table 2 respectively.

**Table 1** GARCH Estimation Results for IDXEnergy

<table>
<thead>
<tr>
<th>Optimal Parameters</th>
<th>Energy Index Volatility GARCH Model (Model 1)</th>
<th>Volume variable (Model 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>( \text{Pr}(&gt;</td>
</tr>
<tr>
<td>Mu</td>
<td>0.000157</td>
<td>0.180428</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.047825</td>
<td>0.440773</td>
</tr>
<tr>
<td>Omega</td>
<td>0.000057</td>
<td>0.023613</td>
</tr>
<tr>
<td>Alpha1</td>
<td>0.063591</td>
<td>0.211635</td>
</tr>
<tr>
<td>Beta1</td>
<td>0.471831</td>
<td>0.013692</td>
</tr>
<tr>
<td>Vxreg1</td>
<td>0.001157</td>
<td>0.180428</td>
</tr>
<tr>
<td>LogLikelihood</td>
<td>796.111</td>
<td>635.3866</td>
</tr>
</tbody>
</table>

The results of the study reveal that there is a positive relationship of 0.001247 between volatility and Covid-19 cases (vXreg1) in Model 1. The sign displayed in the table indicates that this relationship is statistically significant, with a value less than 0.05, which is the confidence level. The P-values of Mu and ar1 are 0.10249 and 0.15776 respectively, indicating that they are not significant in the model.

Both Beta and Omega coefficients have positive values and are considered significant in the model. This suggests that the first difference for the variance coefficient is significant in representing the model and can affect volatility.

However, the Alpha coefficient, with a value of 0.0636, has a P-value of 0.211, indicating very low significance in the model. This indicates that the coefficient of residual for the past period has little effect on the volatility of the Energy Index. The model has a Loglikelihood of 796.111, which should be compared with other models to assess the goodness of fit of variables. In contrast, the results for Model 2, which employs the Volume variable, show no significance in the model for the volatility of the Energy Index. The P-value of the external regressor is 1.00, indicating no significance at all, likely due to the 0 value coefficient. The Mu and ar1 in this model also have no significance, with P-values of 0.069885 and 0.466122 respectively. However, results for Alpha, Beta, and Omega show high significance with all positive relationships with volatility. Omega is estimated to be 0.041727. The coefficient Alpha is 0.341783 with a significance of 0.009119, while Beta is 0.56416 with 0.000001 significance. Alpha and Beta have relatively high coefficient values, implying a high effect on volatility. Notably, Beta has very high significance in the model and the highest coefficient. Loglikelihood with the volume variable has a result of 635.3866. Overall, Model 1 is a better fit than Model 2.

**Table 2** GARCH Estimation Results for IDXTechno

<table>
<thead>
<tr>
<th>Optimal Parameters</th>
<th>Technology Index Volatility GARCH Model (Model 4)</th>
<th>Volume variable (Model 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>( \text{Pr}(&gt;</td>
</tr>
<tr>
<td>Mu</td>
<td>0.001025</td>
<td>0.520184</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.14264</td>
<td>0.083322</td>
</tr>
<tr>
<td>Omega</td>
<td>0.000246</td>
<td>0.000016</td>
</tr>
<tr>
<td>Alpha1</td>
<td>0.375463</td>
<td>0.027458</td>
</tr>
<tr>
<td>Beta1</td>
<td>0.00000</td>
<td>0.999999</td>
</tr>
</tbody>
</table>

Moving on to Model 3, which examines the volatility of the Technology Index with the Covid-19 case variable as vxreg1, the coefficient of the Covid-19 variable is 0.006008 with a significance level of 0.003212. This indicates a minimal positive relationship between Covid-19 cases and volatility, but with high significance. In this model, Mu and ar1 also have no significance, with P-values of 0.520184 and 0.083322 respectively. The Omega coefficient indicates high significance with a P-value of 0.000016 and a value of 0.000246, indicating a low constant value in the highly significant model. The coefficient Alpha has a value of 0.375463 and a P-value of 0.027458, indicating that the change in residuals positively impacts the volatility with high significance to the model. As for the Beta coefficient, the value is 0.00000 with a P-value of 0.999999, indicating that volatility in the previous date has no significance in the model. Loglikelihood is indicated to be 638.7586, which can only be compared between all the other models.

Finally, in Model 4, it can be concluded that all the coefficients in the GARCH model have high significance, as Omega, Alpha, Beta, and vxreg1 coefficients have a P-value of 0.00000. However, Mu and ar1 have P-values of 0.10249 and 0.15776 respectively.

In the literature review section, previous studies have suggested that the Covid-19 pandemic had a positive impact on technological stocks but a negative impact on energy stocks. Our model estimations support these findings, showing favorable results for the Covid-19 variable on both indices. The external regressor coefficient for Covid-19 in models 1 and 3 is highly significant with P-values below 0.05, indicating that Covid-19 cases have significantly influenced investor sentiment.

However, there is a notable difference in the coefficient values between Model 1 (energy sector) and Model 2 (technology sector), suggesting that the impact of Covid-19 on volatility is more significant in the technology sector. This difference may be attributed to
the disparity in the number of listed companies in the energy and technology indices. Currently, the energy index includes 66 listed companies, while the technology index has only 16. With fewer companies in the technology index, the volatility tends to be averaged out.

Additionally, the energy sector index has been established in the Indonesian stock market for a longer period compared to the technology sector, making it less volatile and more predictable. Investors are accustomed to its movement patterns. The coefficients and significance levels in models 1 and 3 differ due to the inclusion of different variables. For instance, the beta coefficient in Model 3 is 0.0000 with a P-value of 0.99999, indicating that past variance has no impact on current conditional variance when the Covid-19 variable is included.

To determine the better-fitting GARCH model, we can consider the Loglikelihood value, which indicates that Model 1 is a better fit than Model 2. Therefore, we reject the hypothesis that the impact of Covid-19 on return volatility is weaker in the technology index than in the energy index.

Regarding the second hypothesis, which considers the volume variable as an external regressor, Model 2 and Model 4 are employed. In Model 2, the coefficient for the volume variable is 0.0000 with a P-value of 1.0000, suggesting no impact on the variances of the energy stock index. However, in Model 4, the coefficient for the volume variable is 0.00019 with a highly significant P-value of 0.00000, indicating a slight positive relationship with volatility.

Both models show high significance in the Omega, Alpha, and Beta coefficients. Among them, Beta stands out with relatively high values. Specifically, Beta in Model 2 is 0.56416, and in Model 4, it is 0.535724, indicating a high persistence of volatility. The Loglikelihood suggests that Model 4 is a better fit overall.

In conclusion, the volume variable has a greater impact on volatility in the technology index compared to the energy index, as supported by the results. The volume variable has no impact in Model 2. The Loglikelihood values further confirm the best fit models. Model 2 is the least favorable, considering the volume variable's lack of impact, while Model 4 shows the highest best fit. Consequently, we accept the hypothesis that the effects of volume on return volatility have a stronger impact on the technology index than on the energy index.

5 Conclusion and Recommendations

The empirical study yielded interesting findings regarding the Volatility and impact of Covid-19 on two specific Indonesian stock indices. The results indicate a positive relationship between Covid-19 cases and Volatility in both the technology and energy indices, although the impact is relatively small. Surprisingly, the Volatility in the technology index was more affected by the Covid-19 variable compared to the energy index. This could be attributed to the different nature and characteristics of the two sectors in Indonesia, with the technology sector being smaller and less mature than the energy sector, which consists of a larger number of listed companies.

Additionally, unexpected results were observed regarding the relationship between Volume and Volatility. While previous studies have shown a positive relationship between the two, it was found that volume had no impact on the Volatility of the energy stock index. On the other hand, volume had a significant yet small impact on the Volatility of the technology stock index. This discrepancy raises questions about the anomalies in the volume data of the energy stock index or the limitations of the model used, which should be considered in future research.

In conclusion, these empirical findings provide valuable insights for investors in Indonesia regarding the volatility impact of Covid-19 on the technology and energy indices. They also highlight the differences between the growing technology sector and the developed energy sector in Indonesia, shedding light on the effects of adverse situations such as the Covid-19 pandemic on these sectors. The study suggests that the technological sector will continue to outpace the energy sector's growth in the coming years due to its ongoing development.

Moreover, these findings serve as an early empirical study on the long-term effects of Covid-19 on specific sectors, offering guidance for investors and researchers. While the study provides satisfactory results in confirming the impact of Covid-19 on Volatility in the two stock indices, there are limitations that need to be addressed. Firstly, the unavailability of historical data for the new indices and the presence of individual listed companies with low stock prices could result in anomalies in the models. Secondly, the standard GARCH model used may have limitations in capturing asymmetric returns and accommodating high fluctuations in uncertain times.

References

7. C. Hiemstra, J. Jones, Testing for linear and nonlinear Granger causality in the stock price-volume relation, Jour. of Fin. 49 (1994)


