Int. Journal of Economics and Management 18 (3): 359-372 (2024)

IJEM
International Journal of Economics and Management
Journal homepage: http://www.ijem.upm.edu.my

The Impact of Asymmetric Price Limits on Stock Portfolio Returns: Evidence from Indonesian Markets

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ABSTRACT

This study examines the effect of asymmetric price limits policy on stock portfolio returns represented by equity mutual funds. An event study methodology was used to calculate abnormal returns (ARs) across four estimation models: constant mean, market-adjusted return, market model, and capital asset pricing model. The sample consists of 237 equity funds in Indonesia, with 7,968 observations in the estimation window and 4,977 in the event window. Statistically significant Average Abnormal Returns (AARs) and Cumulative Average Abnormal Returns (CAARs) were found through parametric and non-parametric tests. The findings are consistent with panel data analysis results. An increase in average returns and a decrease in standard deviation were found for sampled equity funds following the policy implementation. These findings highlight the importance of policy interventions in stabilizing financial markets during crises and offer valuable insights into stock portfolio performance before and after the policy.

JEL Classification: G01, G11, G14, G23

Keywords: Equity Funds; Stock Portfolio; Asymmetric Auto Rejection; Abnormal Return

Article history:
Received: 3 July 2024
Accepted: 25 November 2024

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DOI: http://doi.org/10.47836/ijeam.18.3.05

INTRODUCTION

On January 30, 2020, the World Health Organization (WHO) announced the COVID-19 pandemic as a global emergency, with a high risk of transmission (WHO, 2020). The pandemic has caused severe disturbances to the health sector and the global economy. The effects of the pandemic on the economy have been widespread, where various financial instruments such as stocks, bonds, and commodities have also been affected. The stock markets performance has been particularly affected, with increased pressure. volatility, and uncertainty. In light of such disturbances, policymakers worldwide have taken various measures to mitigate the negative impacts of the pandemic on the stock markets.

In Indonesia, as in many other countries, the pandemic has left a significant impact on the stock market. The Jakarta Composite Index (JCI), the primary stock market index in Indonesia, has experienced a sharp decline, leading to losses and weakened investor confidence in the market. In response, the authorities have implemented various policies to reduce the pressure and stabilize the market. The Financial Services Authority issued an order on March 12, 2020, directing a change in auto rejection and pre-opening mechanism to the Indonesia Stock Exchange (IDX). Following this directive, the Board of Directors of the Indonesia Stock Exchange issued a decree introducing a price limit, which aims to reduce the downside risk faced by the stock market and mitigate the negative effects of the pandemic (IDX, 2020b). The Jakarta Automated Trading System (JATS) will automatically reject a buying or selling offer if the share price falls within the parameters specified in Table 1. This policy went into effect on March 13, 2020.

Table 1 Auto Rejection Ceiling and Floor Limits

Stock Price	Auto Rejection Ceiling Limit	Auto Rejection Floor Limit
IDR 50 - IDR 200	35%	-7%
IDR 200 - IDR 5,000	25%	-7%
> IDR 5,000	20%	-7%

The impact of COVID-19 on stock markets volatility and performance has been extensively studied in recent research. However, much of the existing literature concentrates on the pandemic's influence on individual stock or overall market behavior. It leaves the gap for studies addressing the effects of specific policies in mitigating the impact of pandemic on stock portfolios, especially on the long-term effects of these policies. The price limit policy remained in effect until September 2023 and might have impact beyond typical corporate events. This underscores the need for further research into policy-driven dynamics affecting stock portfolios.

The objective of this study is to conduct a comprehensive analysis of the effect of the asymmetric price limits policy on the performance of equity funds as a proxy of a stock portfolio. The study employed an event study methodology to measure the abnormal returns of the sampled equity funds during the policy implementation. Given that the policy limits the downside risk asymmetrically to the upside risk, the study attempted to assess if fund managers can leverage the opportunity of reduced risk to deliver higher returns for investors. The findings of this study will provide markets stakeholders with valuable insights into the effects of the asymmetric price limits policy in the stock market to stock portfolio returns. It will enable them to make informed decisions during economic stress.

REVIEW OF LITERATURE

The impact of major events on stock markets has been widely studied, with recent focus on the COVID-19 pandemic. Singh et al. (2020) found negative abnormal returns in G-20 countries, including Indonesia, using an event study approach. Setiawan et al. (2021) confirmed this pattern in Indonesia and Hungary, showing that the pandemic caused larger stock market declines than the global financial crisis. Other studies have examined specific sectors, such as large-cap stocks (Nurhayati et al., 2021), Islamic stocks (Cipto et al., 2024), and insurance companies (Farooq et al., 2021) in Indonesia. Geopolitical risks have also affected stock markets. Agyei (2023) noted high volatility due to the Russia-Ukraine conflict, while Boubaker et al. (2022) found negative returns from the invasion, with varied effects across markets.

Several studies have explored the impact of policies on markets. Rahim et al. (2021) found significant abnormal returns and volume changes from trading halts in Indonesia. Indupurnahayu et al. (2022) and Junus and Irwanto (2021) identified notable differences in abnormal returns from bank mergers following the Extensible Business Reporting Language (XBRL) adoption. Behera et al. (2024) showed that monetary stimulus boosted stock returns in Indonesia, and Pramana (2023) found that the asymmetric auto rejection policy affected liquidity and trading volume in LQ45 index stocks. The LQ45 index is one of the major indices on the Indonesia Stock Exchange, consisting of 45 of the largest company stocks. As of May 31, 2024, all stocks in the LQ45 accounted for 48.73% of the IDX market cap (IDX, 2024).

However, the effect of such mitigation policy the in the stock market on stock portfolios remains underexplored. Especially when the policy exists over an extended period. This study aims to address this gap by examining the impact of the asymmetric price limits policy on equity mutual funds, which must hold at least 80% stocks. The null hypothesis for this study is that the asymmetric price limits policy has no significant impact on stock portfolio returns. The findings will provide insights into how policy interventions affect portfolio performance and market stability.

RESEARCH METHODOLOGY

Methodology

The event study methodology is a powerful tool used to assess the impact of an event on security returns during a specific period. MacKinlay (1997) provided a comprehensive review, tracing its application in finance back to early studies like Dolley (1933) who examined stock returns after stock splits. Key improvements in the effectiveness of the method came from works like Ball and Brown (1968), Brown and Warner (1980), and Fama et al. (1969). Event studies have since expanded into the field of economics, as documented by (Currie et al., 2020) reflecting its growing use in top economic journals. However, while event studies are effective in estimating ARs, Miller (2023) highlighted potential biases arising from model selection and emphasized the need for transparency in model explanation and the inclusion of alternative models. To mitigate these risks, this study employs the method developed by Kaspereit (2019) which allows for the computation of multiple sub-event windows and conducts statistical significance tests across four estimation models.

While traditionally used to analyze corporate events on stock market performance, recent studies have demonstrated the methodology's applicability to non-corporate events such as global pandemics (Liu et al., 2020; Pandey and Kumari, 2021), geopolitical risks (Agyei, 2023; Boubaker et al., 2022), and policy changes in specific markets (Guo et al., 2020; Haitsma et al., 2016). In this study. event study methodology will be used to examine whether portfolio managers can achieve higher returns when downside risk is capped at a lower level than the upside due to the price limit policy.

Estimation Model

<u>Equity mutual fund actual return</u>

The monthly return of equity mutual fund (*i*) in month (*t*) was calculated using equation (1):

$$R_{i,t} = \left[\frac{P_{i,t}}{P_{i,t-1}}\right] \tag{1}$$

where $P_{i,t}$ denotes the unit price for equity fund (*i*) at the end of month (*t*) that was calculated as per equation (2):

$$p_{i,t} = \frac{NAV_{i,t}}{unit_{i,t}} \tag{2}$$

where $NAV_{i,t}$ and $unit_{i,t}$ are the net asset value and share unit of equity fund (*i*) in month (*t*), respectively.

Equity mutual fund expected return

This study used several models to calculate the expected return of an equity fund. Should there be no impact of the policy, the return of the equity mutual fund in the event window is expected to be equal to the return as calculated by the model in the estimation window.

Constant Mean Return Model

In this model, the expected return of equity fund (*i*) was calculated following equation (3):

$$E(R_{i,t}) = \bar{R}_{\iota} \tag{3}$$

where $\bar{R}_{\iota}$ is the average of the equity fund return in the specified estimation window, which in this case followed equation (4):

$$\bar{R}_{\iota} = 1/N \sum_{-39}^{-3} R_{i,t} \; for \; i = 1,2,3,4, \ldots., N \tag{4}$$

Market-adjusted Return Model

In this model, the expected return is equal the market return on the event date, which refers to equation (5). The utilization of the market-adjusted return approach did not require the need for an estimation period. This model assumed that the market was efficient, and the average return of the fund would be the same as the market return.

$$E(R_{i,t}) = R_{m,t} \tag{5}$$

Market Model

The market model was used to calculate the expected return based on a single-factor market model. The equity fund return in the estimation window was utilized to estimate the expected return of the market using Ordinary Least Square (OLS) regression. This technique was employed to regulate the relationship between a particular equity fund's return and those of the markets or to account for risk fluctuations associated with the fund. The expected return was computed using equation (6).

$$E(R_{i,t}) = \alpha + \beta Rm_t \tag{6}$$

Capital Asset Pricing Model (CAPM)

CAPM is a method that calculates an asset's expected return based on its beta, the risk-free rate, and the expected market return. The model assumed that the expected return was a function of the risk-free rate of return and the market risk premium, as shown in equation (7). The model also evaluated the level of risk associated with a specific equity fund, assuming that an investor required a higher return to compensate for greater risk.

$$E(R_{i,t}) = Rf_t + \beta(Rm_t - Rf_t) \tag{7}$$

Abnormal Return (AR)

The AR of equity fund (*i*) for month (*t*) was calculated using equation (8), where the expected return would vary for each model.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{8}$$

AARs were calculated as the arithmetic average of ARs for all the equity funds in each month specified in the event window as per equation (9). *N* represents the number of equity funds.

$$AAR_t = 1/N \sum_{\mathrm{i}=1}^{N} AR_{i,t} \tag{9}$$

Cumulative Abnormal Return (CAR)

Equation (10) was used to calculate the CAR of equity fund (i) in the specified sub-event windows from t0 to t+1. The CAR measured the total return obtained by an investor who held an equity fund from the beginning of the event window to the conclusion of a specified post-event window. The abnormal return was calculated for each month, but in an event study, it is necessary to aggregate the return over the event window. Thus, the average of each month's abnormal return over the event window was utilized to determine the CAR.

$$CAR_i(t_0, t_1) = \sum_{t=t_0}^{t_1} AR_{i,t} \tag{10}$$

To investigate the accumulated impact of an event during a specified period, the CAAR was obtained. CAAR referred to the aggregate of monthly AARs for the pre-defined event window (t0–t1). The CAAR for the pre-specified window was calculated as per equation (11).

$$CAAR(t_0, t_1) = \sum_{t=t_0}^{t_1} AAR_t \tag{11}$$

Significance tests

T-test is commonly used to measure the significance of ARs or changes in variance of returns. This test involves calculating the test statistic and comparing it to the absolute value. The absolute value for a 0.05 level of significance is 1.96, which is derived from the standard normal distribution with a mean of 0 and a standard deviation of 1.95%. If the absolute value of the test statistic is greater than 1.96, then it can be concluded that the average abnormal return is significantly different from zero at the 0.05 significance level. In other words, 95% of the distribution falls within the range of ±1.96.

The significance of the coefficient of AAR in event month (t) was calculated as:

$$t - Test_{AAR} = AAR/\sigma(AAR_t) \tag{12}$$

The standard deviation was calculated using the time series of AARs of the estimation period, as shown in equation (13):

$$\sigma(AAR_t) = \sqrt{\sum_{-39}^{-3}(\overline{AR_t} - \overline{\overline{AR}})^2/36} \tag{13}$$

$$\text{where } \overline{\overline{AR}} = 1/36 \sum_{-39}^{-3} \overline{AR_t} \tag{14}$$

$$\text{and } \overline{AR_t} = 1/N \sum_{i=1}^{N} AR_{i.t} \tag{15}$$

On the other hand, the statistic of CAAR for a particular event window (t_1–t_2) was calculated as:

$$t - Test_{CAAR} = \sqrt{\frac{CAAR(t2-t1+1)}{\sigma(AARt)}} \tag{16}$$

According to Serra (2004), t-test measures parametric tests only. This study also applied other main parametric and non-parametric tests. Other parametric tests include the Standardized Residual Test (Patell, 1976) and the Standardized Cross-Sectional Test (Boehmer *et al.*, 1991). The non-parametric tests include the Generalized Sign Test (Cowan and Sergeant, 1996; Sanger and Mc Connell, 1986) and the Wilcoxson Signed Rank Test.

DATA AND EVENT OF INTEREST

Sampling and Data Collection

Monthly data of all available equity mutual funds were collected from the Financial Services Authority (OJK) website for the period from December 2016 to December 2021. As of March 31, 2020, there were 321 equity funds (OJK, 2023), but not all provided sufficient data in the required level of detail for the defined estimation window. Some funds experienced sudden changes in Net Asset Value (NAV) or inconsistent data due to liquidation from insufficient subscription thresholds. Following Harrell (2016), to ensure statistical accuracy, the sample was filtered to include funds with a minimum of 12 observations. The final sample consisted of 237 equity funds, totaling 7,968 observations in the estimation window and 4,977 in the event window. Additionally, market data were collected from the Indonesia Stock Exchange (IDX, 2023), and the Indonesia 10-Year Bond yield was used for the risk-free rate, sourced from a third-party provider (Investing, 2023).

Event Window

On March 13, 2020, an asymmetric price limits policy came into force (IDX, 2020b). As available data from the Financial Services Authority in the form of monthly data for equity funds were provided on the last trading day of the month (e.g., March 31, 2020), March 2020 was selected as t_0 or the event month in the analysis.

To examine the effect of the asymmetric price limit policy on equity fund returns, the event window spanned 21 months, including 20 months after the policy implementation and the announcement month (t_0 - t_{+20}), as depicted in Figure 1. For CAAR analysis, the entire event window was divided into seven segmented sub-event windows: 0–2 months, 3–5 months, 6–8 months, 9–11 months, 12–14 months, 15–17 months, and 18–20 months. Each sub-event window comprised a three-month observation period. For comparison, CAARs were also calculated for roll-up windows from the month of policy implementation on the seven sub-event windows as well: 0–2 months, 0–5 months, 0–8 months, 0–11 months, 0–14 months, 0–17 months, and 0–20 months.

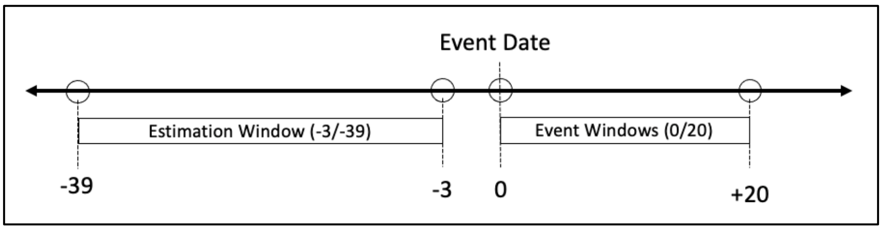


Figure 1 Event and Estimation Windows of the Asymmetric Price Limits Policy

Estimation Window

This study defined an estimation window covering a three-year period prior to the event date spanning from December 2016 to December 2021 (t_{-39} to t_{-3}) as indicated in Figure 1. This window was expected to provide a sufficient sample size to account for any past trends and fluctuations in the equity fund returns. The approach follows MacKinlay (1997), ensuring the event window is larger than the period of interest to capture market activity surrounding the event. However, a two-month gap (January and February, 2020) was left out between the estimation window and the event window to minimize any noise in the results. This exclusion is essential, given potential noise from market behaviour due to the COVID-19 pandemic.

RESULTS AND DISCUSSION

Mean Returns and Standard Deviations

Table 2 presents the mean returns and standard deviations of equity funds. The table reports both pre-event and post-event means and standard deviations. The findings revealed that the equity funds experienced negative overall mean returns before and after the event. However, the value of post-event mean return (-0.19%) was higher than the pre-event mean return (-0.90%). The overall and within standard deviation of equity funds were higher after the event. Nevertheless, the standard deviation between the equity funds after the event was lower, perhaps implying a reduced level of risk. The post-event average market return (0.31%) was positive and higher than the pre-event average market return (-0.25%). The risk-free rate was lower post-event (0.55%) than the risk-free rate pre-event (0.61%).

Table 2 Average returns and standard deviations before and after the event

Variable		Mean	Std. dev.	Min	Max
EF Return pre-event	overall	-0.00897	0.05386	-0.90762	1.43598
	between		0.01279	-0.08419	0.04248
	within		0.05245	-0.89738	1.38453
EF Return post-event	overall	-0.00185	0.07270	-0.58739	0.50408
	between		0.00871	-0.04749	0.03832
	within		0.07218	-0.54175	0.54971
Market Return pre-event	overall	-0.00247	0.02684	-0.06942	0.06036
Market Return post-event	overall	0.00307	0.05659	-0.18999	0.08508
Risk Free Rate pre-event	overall	0.00609	0.00049	0.00523	0.00714
Risk Free Rate post-event	overall	0.00554	0.00044	0.00494	0.00657

displays the monthly returns distribution pattern of 237 equity funds in the specified estimation windows (t_{-39} – t_{-3}). The graph indicates that the equity fund returns were normally distributed around the mean. However, the presence of long tails on the left and right ends of the graph, as seen in the observation windows t_{-4}, t_{-13}, t_{-18}, and t_{-37}, suggests the occurrence of unusual returns of certain equity funds. The long tails on the normal distribution graph occurred due to the presence of extreme events or outliers that significantly impacted the performance of certain equity funds. This was caused by the significant increase or decrease in NAV or investment unit due to extreme events. Several factors such as consolidation of asset and write-off leading to significant fluctuations in specific equity fund returns might be responsible.

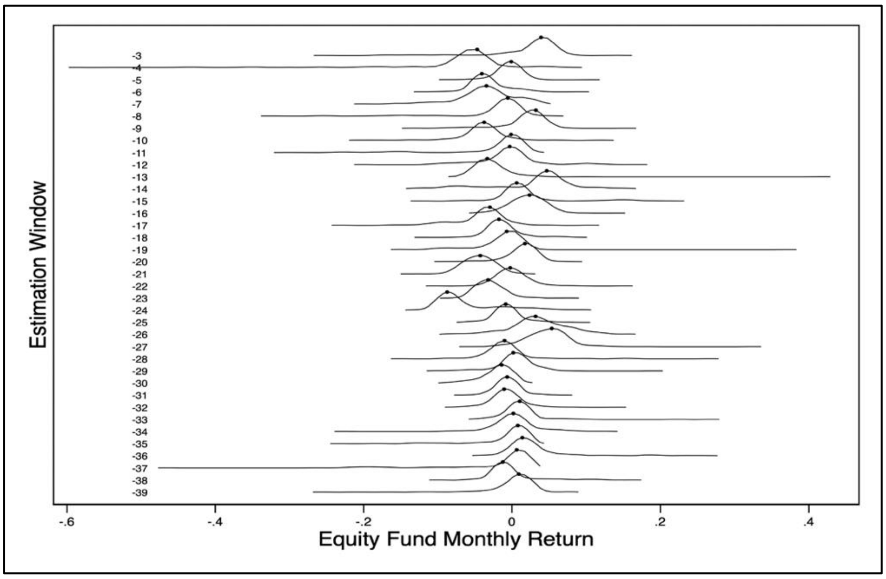


Figure 2 Distribution of equity fund monthly returns during the specified event window

Average Abnormal Returns (AARs)

Table 3 presents the results of the AARs analysis of the four estimation models on the observation windows starting from the event month (t_0) followed by the subsequent months (t_{+1} – t_{+20}). The findings indicated that the constant mean model, as well as the CAPM and market model, exhibited negative AARs (-17.64%, -5.42%, and -5.28%, respectively) on the event month. Specifically, the actual average return in t_0 was lower by 17.64% for the constant mean model compared to the average return in the estimation windows. Equity funds suffered substantial losses in t_0, associated with March 2020, compared to their average return in the previous months.

However, the market-adjusted model exhibited a positive AAR (0.47%) in t_0. This finding suggests that the average equity funds return in the event month is higher than the market return. The monthly return of the Jakarta Composite Index by the end of March 2020 (associated with t_0) was recorded as -19.00% (IDX, 2020b). It implies that even though, on average, equity funds experienced substantial losses, they were able to minimize the impact of the crisis. The highest AAR (9.54%) for the constant mean model was recorded in t_{+8} (associated with November 2020). The return is significantly higher compared to the market return, represented by the Jakarta Composite Index, for the same month recorded as 1.14% (IDX, 2020c).

Table 3 Average normal return in the specified event window

t	AAR Constant Mean	AAR Market Adjusted Return	AAR Market Model	AAR CAPM
0	-0.176426	0.004684	-0.005418	-0.005280
1	0.029626	-0.011039	-0.000800	-0.000874
2	0.008227	-0.001941	0.005501	0.005497
3	0.039183	0.005443	0.015047	0.015030
4	0.038168	-0.012732	-0.001554	-0.001557
5	0.018184	-0.001235	0.007056	0.007079
6	-0.067202	0.003418	0.003450	0.003556
7	0.047281	-0.006687	0.004773	0.004782
8	0.095437	0.002906	0.017903	0.017907
9	0.063202	-0.002392	0.010134	0.010182
10	-0.036324	-0.018919	-0.014006	-0.013902
11	0.047588	-0.017439	-0.004965	-0.004965
12	-0.044367	-0.004753	-0.001877	-0.001793
13	0.002672	-0.001323	0.005553	0.005621
14	-0.003712	0.002042	0.008024	0.008103
15	-0.015203	-0.023886	-0.016580	-0.016529
16	0.008028	-0.008309	-0.000301	-0.000232
17	0.019215	0.003770	0.011696	0.011782
18	0.022764	-0.001520	0.007217	0.007274
19	0.038011	-0.011581	-0.000523	-0.000476
20	-0.008361	-0.001922	0.003997	0.004090

The table also indicates that the constant mean model reported positive AARs for 14 out of 21 sub-event windows, suggesting that the average returns of the equity funds in those months were higher than the average returns in the sub-estimation windows. In contrast, the market-adjusted return model reported negative AARs results in 15 out of 21 sub-event windows. The CAPM and market model reported similar results, with positive AARs in 12 out of 21 sub-event windows.

Figure 3 presents that the trend of AARs for equity funds from t_0 to t_{+20} showed a wide variation when using the constant mean model. In contrast, the market-adjusted model and CAPM offered minimal variations. However, as the market model and CAPM had minor differences in AARs, they appeared to overlap on the graph. The constant mean model was more sensitive in measuring the return of the stock portfolio in the event windows. The constant mean model, which assumed a constant mean return for all equity funds in the estimation windows, was found to be able to capture the individual portfolio effects during the events. In contrast, the market-adjusted model, which considered the overall market performance beyond the equity funds, was less sensitive to individual observed portfolio effects (idiosyncratic risk). The single-factor market model and CAPM, which considered both market and individual portfolio effects, might offer a more comprehensive analysis of market events. These findings suggested that the choice of model could significantly affect the AARs result. Depending on the level of granularity required, it is essential to consider the appropriate model for proper analysis.

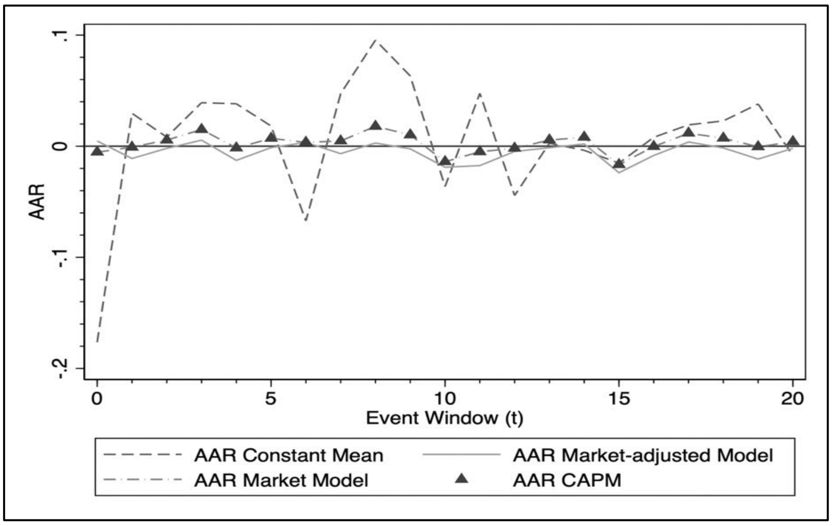


Figure 3 Average abnormal returns in the event window

Cumulative Average Abnormal Returns (CAARs)

Monthly AARs corresponding to the equity funds were aggregated to derive CAARs. Table 4 CAARs results for various estimation models depicts the CAARs of the 237 equity mutual funds for the entire event windows ($t_0 - t_{+20}$). CAARs were calculated using two approaches: panel A for segmented sub-event windows and panel B for rolling sub-event windows from the event date. The purpose of these two panels is to analyze CAARs across different holding periods.

In panel A of Table 4, the results indicated that during the first three-months period (t_0 - t_{+2}) the equity funds experienced negative CAARs for all estimation models, reflecting the aftershock of the pandemic on the capital markets. However, in the next three-months period sub-event window (t_{+3} - t_{+5}), the equity funds generated positive CAARs in the constant mean model, market model, and CAPM. Nevertheless, the CAARs in the market-adjusted return model still showed a negative return, suggesting that the average equity fund net return is still below the market return. The constant mean model showed that five out of seven three-month sub-event windows generated positive CAARs, while the CAPM and market model resulted in four out of seven three-month sub-event windows with positive CAARs. In contrast, the market-adjusted return model showed negative CAARs in all three-month sub-event windows.

Based on these findings, it can be concluded that the constant mean model exhibited a relatively stronger performance in generating positive returns during the segmented three-month sub-event windows compared to the other models, while the market-adjusted return model struggled to generate positive returns. Furthermore, the results in panel A showed that the equity funds experienced a negative impact from the pandemic during the initial three-month period, but a recovery was observed during the subsequent three-month periods.

Table 4 CAARs results for various estimation models

t	CAAR Constant Mean Model	CAAR Market Adjusted Return	CAAR Market Model	CAAR CAPM
Panel A: Individual sub-event window				
[0;2]	-0.138573	-0.008296	-0.000718	-0.000657
[3;5]	0.095534	-0.008524	0.020549	0.020552
[6;8]	0.075516	-0.000363	0.026126	0.026244
[9;11]	0.074466	-0.038750	-0.008837	-0.008685
[12;14]	-0.045406	-0.004033	0.011700	0.011932
[15;17]	0.012041	-0.028425	-0.005185	-0.004979
[18;20]	0.052415	-0.015023	0.010691	0.010889
Panel B: Rolling sub-event window				
[0;2]	-0.138573	-0.008296	-0.000718	-0.000657
[0;5]	-0.043039	-0.016820	0.019832	0.019896
[0;8]	0.032477	-0.017182	0.045957	0.046140
[0;11]	0.106943	-0.055933	0.037120	0.037455
[0;14]	0.061537	-0.059966	0.048820	0.049387
[0;17]	0.073578	-0.088391	0.043635	0.044408
[0;20]	0.125993	-0.103414	0.054326	0.055297

In panel B of Table 4, AARs were aggregated into seven rolling windows. In the first three-month period after the policy implementation (t_0 - t_{+2}), all models indicated negative returns for equity funds. However, in the six-month period (t_0 - t_{+5}), both the CAPM and market model showed positive CAARs, indicating that subsequent months' returns offset the initial three-month losses. In the constant mean model recorded positive CAAR in the nine-month period (t_0 - t_{+8}), with the highest CAAR of 12.60% observed over the 21-month period (t_0 - t_{+20}). The CAPM resulted in CAARs values similar to those of the market model in a 12-month period (t_0 - t_{+11}), with 3.71% and 3.75%, respectively. Notably, the market-adjusted return model consistently reported negative returns across all rolling windows with CAAR of -10.34 %over the 21-month period.

Figure 4 displays the CAARs over the sub-event windows, providing insights into the performance of different estimation models in generating abnormal returns for equity funds upon asymmetric price-limit policy implementation. The constant mean model exhibited the lowest CAAR at the beginning of the event windows but resulted in the highest CAAR by the end of the windows. These findings may be attributed to the policy implementation, which resulted in significant abnormal returns for the equity fund compared to their returns before the policy implementation. Although the CAPM and market model offered positive CAAR results by the end of the event windows, the magnitude of the returns was lower than that of the constant mean model. In contrast, the market-adjusted return model started with a positive CAAR at t_0 but ended with the

lowest CAAR at t_{+20}, indicating a weaker performance in generating positive returns compared to other models. These findings suggest that the equity funds experienced an increase in their average CAARs after the policy implementation, but their average return remained below the market return.

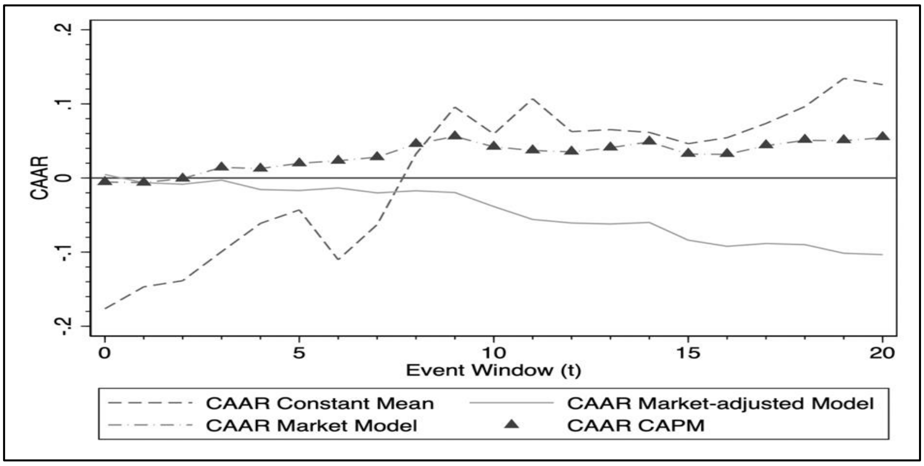


Figure 4 Cumulative Average Abnormal Returns in the Event Windows

Significance tests

This study reports on the results of significance tests conducted on the AARs for each sub-event window using three parametric tests and two non-parametric tests for the four selected models. Figure 5 presents a summary of the obtained results. The t-test conducted on the AARs for the constant mean model showed a significant level of 0.01 in 77% of sub-event windows. Conversely, the t-test for the market-adjusted return model indicated only eight sub-event windows with a significant level of 0.05, of which six sub-event windows had a significant level of 0.01. The findings suggest that the market-adjusted return model was less sensitive in detecting significant abnormal returns when compared to the constant mean model. The t-test results for the CAPM and market model were similar, with both models exhibiting nine sub-event windows having a significant level of 0.05. These findings indicate that both models effectively detected significant abnormal returns. The inclusion of risk-free assets in the CAPM model does not differentiate the significant test result from the market model, which does not account for risk-free assets.

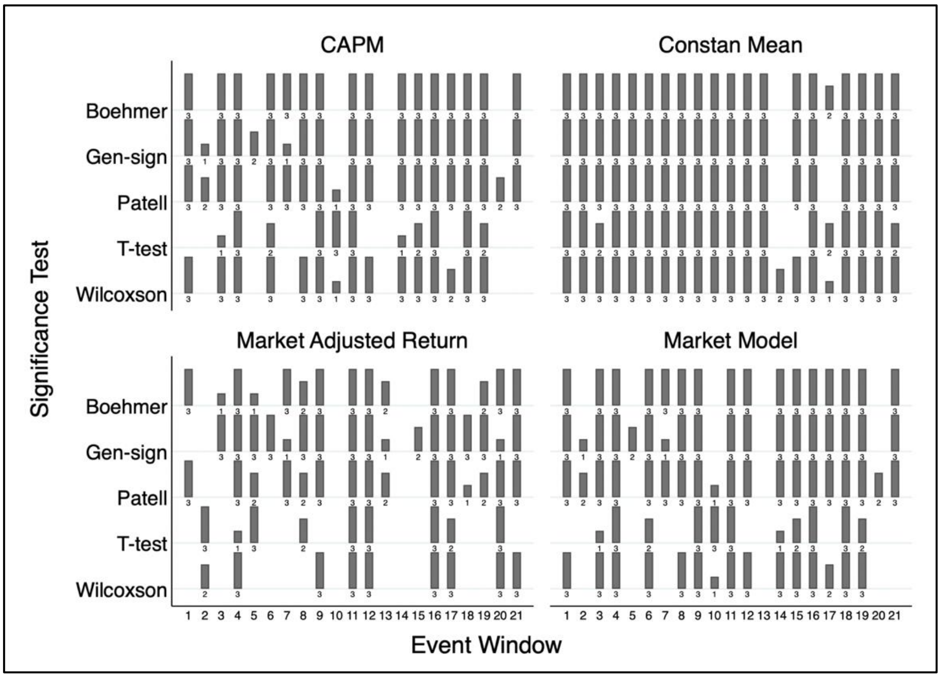
To evaluate the adequacy of the estimation models and the validity of the results, Patell's Standardized Residual Test was conducted. The test results for the constant mean model indicated significant levels of 0.01 for 19 out of 21 sub-events, confirming the model's ability to capture the expected returns and generate accurate results. Significant levels of 0.05 were observed in 14 out of 21 sub-event windows for the market-adjusted model, indicating a relatively weaker performance compared to the constant mean model. Similarly, significant levels of 0.05 were observed in 18 out of 21 sub-event windows for the CAPM and market model, suggesting a slightly weaker performance compared to the constant mean model.

The results on Boehmer's Standardized Cross-Sectional Test indicated that the constant mean model performed the best, with 19 out of 21 sub-event windows showing a significant level of 0.01 and only one sub-event window was found not significant. For the CAPM and market model, significant levels of 0.01 were observed in 16 out of 21 sub-event windows, indicating a slightly weaker performance than the constant mean model. However, the market-adjusted model showed 13 sub-event windows with a significant level of 0.05, and only 10 sub-event windows with a significant level of 0.01. Although all models could detect significant abnormal returns in most sub-event windows, the significance level was slightly higher for the constant mean, CAPM, and market models. However, the market-adjusted model could still provide valuable insights, albeit at a lower significance level.

The non-parametric tests were applied to the calculated AARs for each model. Figure 5 also presents the Generalized Sign Test (Gen-Sign) results. The findings indicate that the constant mean model had the highest significant Gen-Sign Test results, with 19 out of 21 sub-event windows having a significant level of

0.01. The market model and CAPM exhibited slightly lower Gen-Sign significance test results, with 16 out of 21 sub-event windows having a significant level of 0.05. However, the market-adjusted model had the lowest

significant Gen-Sign Test results, with only 14 out of 21 sub-event windows having a significant level of 0.05. The constant mean model is most effective according to the Gen-Sign Test.



Note: Sub-event windows are arranged in sequential order from t_{-0} to t_{+20} as 1 to 21. The value height of the bar associated with number of asterisks of significance level, 1 = * = p < 0.10; 2 = ** = p < 0.05; and 3 = *** = p < 0.01.

Figure 5 Summary of Significance Test Results on the AARs for Each Sub-event Window

The findings of the non-parametric test's Wilcoxon signed-rank test are also shown in Figure 5. The market-adjusted return model had the least significant results, with only 9 out of 21 sub-event windows having a significant level of 0.05. However, the market model and CAPM demonstrated that 14 out of 21 sub-event windows have a significant level of 0.05, which is consistent with the Gen-Sign test results. Additionally, the constant mean model had 20 out of 21 sub-event windows with a significant level of 0.05 and 20 out of 21 sub-event windows with a significant level of 0.01. These results imply that the non-parametric tests yielded comparable outcomes, suggesting that the calculated AARs for all models are statistically significant. Perhaps the constant mean model is the most effective model to be used.

Panel Regression

To evaluate the impact of the policy implementation on the average equity fund return, panel regression analysis was conducted using two models. The market model was used to estimate the average return of equity funds (R_i) using market return (R_m) as the predictor. The results in Table 5 indicates a higher regression slope for the post-event model (0.966) compared to the pre-event model (0.929), suggesting a stronger relationship between market excess return and expected excess return of equity funds. The intercept was also higher for the post-event model (-0.00473) than for the pre-event model (-0.00669), with both regression results statistically significant at the 0.001 level. These findings suggest that for the same 1% increase in market return (Rm), led to an average return of equity funds (R_i) of 0.49% after the event, compared to only 0.26% before the event. It indicates an improvement in the average performance of equity funds. This improvement in the expected return of the equity funds after the event may be attributed to overall changes in the market condition as the impact of the policy implementation.

Table 5 Panel regression of equity fund return by the market return using the CAPM and market model

	Market Model		CAPM	
	Ri (pre-event)	Ri (post-event)	Ri-Rf (pre-event)	Ri-Rf (post-event)
Rm	0.929*** (53.05)	0.966*** (84.68)		
Rm-Rf			0.931*** (53.24)	0.966*** (85.01)
Intercept	-0.00669*** (-8.44)	-0.00473*** (-7.32)	-0.00711*** (-8.82)	-0.00492*** (-7.62)
Observations	7861	4914	7861	4914

Notes: t-statistics in parentheses, they are significant at: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The Capital Asset Pricing Model (CAPM) was employed to estimate the expected excess return of equity funds relative to risk-free assets (R_i-R_f) in a panel regression before and after the policy implementation, with market excess return (R_m-R_f) as a predictor. The results presented in Table 5 indicates a higher regression slope (beta) for the post-event model (0.966) compared to the pre-event model (0.931), suggesting a stronger relationship between market excess return and expected excess return of equity funds. Furthermore, the intercept (alpha) was also higher for the post-event model (-0.00492) than for the pre-event model (-0.00711), and both regression results were statistically significant at the 0.001 level. These findings also imply that for the same 1% market excess return (R_i-R_f), the expected average equity fund relative to risk-free assets return (R_i-R_f) likely results in 0.47% after the event, compared to only 0.22% before the event. As such, the results indicate that the implementation of the policy had a significant effect on the expected return of the average equity fund.

The panel regression results for both the Market model and CAPM indicate positive slopes (beta) that are close to 1, implying that equity funds generally move in the same direction as the market but with lower volatility. This relationship was found to be statistically significant at the 0.01 level for both pre-event and post-event periods. However, a negative intercept (alpha) was observed for both models, either before or after the event, indicating that, on average, equity funds experience inferior returns compared to the market return. Similar finding reported that majority of equity funds fails to deliver positive value-added (Rosidin et al., 2024). This finding aligns with studies in other emerging markets, such as Pakistan (Aqeeq and Chamadia, 2023). The negative alpha may also explain the negative CAAR when using the market-adjusted return model. The study also resonance with Božović (2022) who studied US-based emerging market mutual funds and observed significant negative alpha, driven by losses in underperforming funds. While short-term positive alpha can occur due to momentum in emerging market stocks, in the long term, these funds tend to perform similarly to their developed-market counterparts with average negative alpha.

CONCLUSIONS

This study investigated the impact of the asymmetric price limit policy implemented by the Indonesian Stock Exchange on the extended performance of stock portfolios represented by equity funds. The results indicated that the null hypothesis was rejected, demonstrating that the policy effectively mitigated the crisis's impact on the stock market. Statistically significant AARs and CAARs were observed across the CAPM, average mean return, market-adjusted return, and market models, confirmed by both parametric and non-parametric tests. Most equity funds experienced positive returns post-event, supported by higher average returns and lower standard deviations in the panel data.

This study contributes to the literature on financial regulation and market efficiency, highlighting the importance of policy interventions in mitigating the effects of market crises. The findings have important implications, providing evidence that the asymmetric price limit policy can help reduce the negative impacts of market disruptions. While price limits policy plays a crucial role in maintaining market stability, their design, implementation should be continuously reviewed and updated to ensure effectiveness in an evolving financial landscape.

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