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PENGARUH VOLATILITAS DAN PENURUNAN HARGA TERHADAP PROBABILITAS PEMULIHAN SAHAM *FALLING KNIVES* DI INDONESIA: PENDEKATAN REGRESI LOGISTIK

DO VOLATILITY AND PRICE DECLINE MATTER? EVIDENCE FROM FALLING KNIVES IN INDONESIA USING LOGISTIC REGRESSION

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ABSTRAK

Penelitian ini menganalisis probabilitas pemulihan saham yang mengalami penurunan harga tajam (*falling knives*) di Indonesia pada periode 2010-2020. Menggunakan data Bursa Efek Indonesia, penelitian ini mengidentifikasi 194 kejadian *falling knives* dan mengevaluasi kemampuan saham untuk memberikan *return* positif dalam tiga tahun setelah penurunan harga. Analisis dilakukan menggunakan regresi logistik dengan metode *bootstrapping*, dengan fokus pada determinan berbasis harga, yaitu besarnya penurunan harga dan volatilitas *return*. Hasil penelitian menunjukkan bahwa volatilitas berpengaruh negatif pada probabilitas pemulihan saham. Semakin tinggi volatilitas, semakin kecil kemungkinan saham untuk kembali ke harga sebelum penurunan. Sementara itu, besarnya penurunan harga tidak terbukti berpengaruh secara statistik terhadap probabilitas pemulihan saham. Hasil penelitian ini juga menunjukkan bahwa hanya 22,7% kejadian *falling knives* yang menunjukkan *return* positif secara konsisten dalam periode tiga tahun. Temuan ini mengindikasikan rendahnya saham yang berhasil pulih setelah penurunan tajam. Selain itu, temuan ini memberikan bukti empiris mengenai volatilitas sebagai faktor penting pada pemulihan saham *falling knives*.

Kata Kunci: *falling knives, falling stocks*, volatilitas *return*, *price decline, return* saham

ABSTRACT

This research examines the recovery probability of stocks experiencing sharp price declines or falling knives from 2010 to 2020 in Indonesia. Using data from Indonesia Stock Exchanges, this study identified 194 falling knife observations and evaluated whether the stocks could provide positive returns within three years after the price drop.The analysis uses logistic regression with a bootstrapping approach, focusing on price-based determinants, namely, the magnitude of price decline and return volatility. The results indicate that volatility has a negative impact on the probability of stock recovery. The higher the volatility of a stock, the lower the likelihood that it will return to its pre-decline price. In contrast, the magnitude of the price decline is not statistically associated with recover probability. Furthermore, only 22.7% of falling knives consistently yield positive returns over the three-year period. These findings indicate the

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small number of stocks that recover after a sharp decline. These findings also emphasize the importance of volatility as a key factor in assessing stock recovery probability.

***Keywords**: falling knives, falling stocks, return volatility, price decline, stock returns*

1. INTRODUCTION

Stock price fluctuations are often influenced by external factors. Those factors include macroeconomic conditions, government policies, and changes in the political situation. In Indonesia, the stock market has experienced various important events that have significantly affected stock price movements, including the Asian economic crisis in 1997-1998, the global financial crisis in 2008, and economic pressure due to the COVID-19 pandemic in 2020. These events impact stock price volatility, as seen in Table 1, where stock prices have fallen very sharply.

Table 1

Decline in the Jakarta Composite Index (JCI)

Price	1997/1998 Crisis	2008 Crisis	COVID-19
High	742.9500	2838.4761	6636.3320
Low	255.4590	1089.3400	3911.7161
Change	-65.62%	-61.62%	-41.06%

Source: Yahoo Finance, data processed

As seen in Table 1, these events significantly impacted the Composite Stock Price Index (IHSG). The most significant decline occurred during the 1997/1998 crisis, when the IHSG fell by 65.62%. The data shows how extreme the market price movements were during the crisis. Interestingly, although COVID-19 is a widespread global crisis, its impact on the IHSG was not as severe as the damage brought by the 1997/1998 monetary crisis or the 2008 global financial crash.

This sharp price decline phenomenon in the investment world is often called falling knives. The falling knife refers to the rapid and significant drop in the prices of stocks or other assets. It stems from the well-known phrase among investors, “Do not try to catch a falling knife,” which warns about the dangers of buying stocks during a steep fall, since there is no guarantee; the decline has reached the bottom. However, some investors see opportunities in this condition,

hoping that the stock price will recover soon and generate profits. However, this strategy is full of risks because the stock price could continue to decline.

Sharp stock price declines are often exacerbated by market overreaction and speculative activity (Colliard, 2012). In addition, an investor's psychology is a factor that influences decision-making. Various sentiments can influence investors, including good and bad news. In such conditions, stock valuations can be biased: previously expensive stocks can be considered too expensive (overvalued), and low-priced stocks can appear too cheap (undervalued).

Therefore, many investors rely on a more measured approach to assessing stock potential. According to Fama & French (2004), company size and the ratio of book value to market price provide a reasonable basis for selecting stocks that are expected to return in the future. On the other hand, large-scale external events such as the COVID-19 pandemic have also been shown to accelerate sharp stock price declines (Alber & Saleh, 2020; Baker et al., 2020; He et al., 2020; Kusumahadi & Permana, 2021).

Several empirical studies have examined stock performance after price decline. Brandes Institute (2004) documented positive average returns for falling knife stocks over multi-year horizons, while Kochman and Tompkins (2008) showed that recovery prospects improve when stock selection is guided by firm fundamentals, such as the Altman Z-score. Other studies emphasize the role of volatility and market uncertainty in shaping recovery dynamics (Hamal & Gautam, 2021; Just & Echaust, 2020; Liu & Zhang, 2015; Rakshit & Neog, 2021; Zhao, 2023). However, these studies largely focus on average returns, fundamental factors, or market volatility, without explicitly modeling the probability of recovery after extreme price declines, particularly in emerging markets.

Despite frequent sharp price declines in Indonesia, empirical evidence on falling knife recovery remains limited. Prior studies largely emphasize average returns or firm fundamentals, with less attention to price-based recovery determinants. This study fills this gap by employing a logistic regression approach to estimate recovery probabilities using the magnitude of price decline and return volatility, providing new evidence from the Indonesian market.This study aims to

analyze the performance of falling knife stocks three years after they experienced a sharp price decline. Specifically, the study aims to evaluate whether these stocks have the potential to recover and generate positive returns in the long term or if they continue to weaken and pose a risk to investors. In addition, this study aims to identify factors that can affect the probability of price recovery by analyzing price-based variables such as the magnitude of the price decline and return volatility during the observation period. We expect this study to contribute to the academic literature on the falling knife phenomenon and provide empirical evidence on price recovery determinants in emerging markets.

2. LITERATURE REVIEW AND HYPOTHESIS

Falling Knife Stocks and Post-Decline Recovery

In the stock market, there is a popular expression that emphasizes the importance of not chasing a declining stock. This expression describes the high risk when buying stocks experiencing a sharp decline because the decline has not necessarily reached its bottom. The Brandes Institute (2004) defines the terminology of a falling knife as a stock experiencing a price decline of 60 percent or more over 12 months. Using this definition, the study identified 1,904 U.S. stocks that experienced declines between 1980 and 2000. The performance of these stocks was then tracked over the following three years. The study reports positive average returns of 5.6% and 6.6% over two- and three-year holding periods, respectively. Similar patterns were observed in international markets, where falling knife stocks increased by an average of 10.8% annually over three years, outperforming the corresponding Morgan Stanley Capital International (MSCI) index.

Kochman and Tompkins (2008) conducted a follow-up study on stock selection based on specific criteria. They examined 979 stocks that experienced a decline of 60% or more between 1993 and 2002. To improve the likelihood of recovery, the study filtered firms using the Altman Z-score. The Altman Z-score is a financial distress indicator used to predict bankruptcy risk. Firms with Z-scores above 3.0 indicate relatively strong financial health, and they were included

in the final sample. Three years after the decline, these stocks showed substantial recovery, with average returns that could triple market performance over two- to three-year holding periods.

Recent studies also examine extreme price losses using event-based approaches. Guo et al. (2024), for example, find that extreme loss events are often followed by short-term return reversals, suggesting that sharp declines may be accompanied by partial rebounds. Choi (2021) also finds that drawdown and recovery patterns contain useful information for future performance, indicating that large price declines tend to follow different recovery paths.

From a behavioral perspective, extreme negative price movements may reflect investor overreaction, pushing prices below fundamental values and creating temporary mispricing. Zakamulin (2024) shows that stronger price declines tend to be followed by more pronounced reversal effects, particularly during bearish market conditions. That said, not all rebounds can be attributed only to overreaction. Choi and Jayaraman (2009) argue that short-term reversals may also arise from liquidity effects and information asymmetry, indicating that recovery mechanisms are more complex than behavioral explanations.

Magnitude of Price Decline and Stock Recovery

Results from both studies imply that not all stocks with a significant drop share the same likelihood of recovery. Several factors can influence how likely a stock is to recover. One factor is the magnitude of the decline in the stock price itself. When stocks experience a significant decline, investors often react with caution and fear. This response can lead to increased volatility and reduced interest in reinvesting, ultimately reducing the probability of recovery (Sakamoto & Sengoku, 2021).

Although Brandes Institute (2004) and Kochman and Tompkins (2008) report positive average returns for selected falling knife stocks, their results also point to wide differences in recovery outcomes. In many cases, sharp declines may signal deeper structural problems rather than temporary market overreaction, making price reversals less likely. Sakamoto and Sengoku (2021) further showed that large price drops increase perceived risk and reduce the likelihood of recovery.

Similar patterns appear in drawdown-based and extreme loss studies. Choi (2021) found that deeper drawdowns are typically followed by longer recovery periods, while Guo et al. (2024) showed that extreme loss events tend to produce only partial rebounds, even in the short run. Behavioral evidence also suggest that although large negative shocks often trigger overreaction, they do not necessarily lead to sustained recovery (Zakamulin, 2024).

Return Volatility and Stock Recovery

Return volatility reflects market uncertainty and plays an important role in shaping investor confidence following extreme price movements. High volatility environments are often associated with unstable expectations, elevated risk perceptions, and reduced market participation, all of which may inhibit stock recovery. Just and Echaust (2020) revealed that increased volatility is associated with structural changes in market behavior, which can hinder recovery efforts. Hamal and Gautam (2021) also found that investor confidence tends to decrease when volatility increases sharply, so the probability of price recovery also decreases. Similar results were also found in several studies showing that extreme market conditions, characterized by high volatility, can inhibit stock recovery, especially for stocks that experience significant falls (Liu & Zhang, 2015; Rakshit & Neog, 2021; Zhao, 2023).

Additional evidence from crisis-period studies indicates that idiosyncratic volatility and volatility risk are strongly associated with future stock returns, reflecting heightened uncertainty and risk aversion during turbulent markets (Kongsilp & Mateus, 2017). From a market microstructure perspective, higher anticipated volatility also increases inventory risk faced by liquidity providers, contributing to delayed price stabilization (Bogousslavsky et al., 2025).

Research Hypotheses

H1: The magnitude of price decline has a negative effect on the probability of stock recovery.

H2: Return volatility has a negative effect on the probability of stock recovery

3. RESEARCH METHODS

This study uses secondary data obtained from the Indonesia Stock Exchange (IDX) covering the period from 2010 to 2020. The number of listed companies varies each year, ranging from 355 in 2010 to 658 firms in 2020, resulting in a total of 5,296 firm-year observations during the sample period. Each firm-year observation represents the annual performance of an individual firm in a given year. Annual returns are calculated using the following formula:

$$Return_{i,t} = \frac{Close_{i,t} - Close_{i,t-1}}{Close_{i,t-1}} \quad (1)$$

where:

t refers to the year, ranging from 2010 to 2020

i is the index of a stock that falls under the falling knife category

$Return_{i,t}$ is the return of stock i in year t

$Close_{i,t}$ is the closing price of stock i in year t

$Close_{i,t-1}$ is the closing price of stock i in the previous year $(t-1)$

After obtaining the return data, the data are filtered to identify stocks that meet the criteria of a falling knife, namely, stocks that experience a return decline of -60% or more. After applying the falling-knife criterion, 194 falling-knife observations were identified during the 2010–2020 period. The performance of these stocks is then analyzed for three years after the sharp decline to assess the level of recovery and potential return for investors willing to invest in a falling knife. This study treats each falling knife episode as a separate observation, combining events across years into a single pooled dataset.

Returns in the first, second, and third years after the sharp decline are calculated using the formula:

$$Return_{i,n} = \frac{Close_{i,t_0+n} - Close_{i,t_0}}{Close_{i,t_0}} \quad (2)$$

where:

t_0 is the base year, which is the year when the stock experienced a sharp decline

n is the 1st, 2nd, or 3rd year after the base year t_0

$Return_{i,n}$ is the return of stock i in the n-th year

$Close_{i,t_0}$ is the closing price of stock i in the base year t_0

$Close_{i,t_0+n}$ is the closing price of stock i in the n-th year after the base year t_0

This research method includes descriptive analysis to identify the characteristics of stocks in the falling knife category, as well as the average return of the stocks in the following 3 years. In addition, logistic regression analysis is used to evaluate the effect of the magnitude of the price decline (hereafter referred to as dropsize) and return volatility on the probability of stock recovery. The logistic regression model used is as follows:

$$P(\text{Recovery}_{i,n}) = \frac{e^{\beta_0 + \beta_1 \text{Dropsize}_i + \beta_2 \text{Volatility}_i}}{1+e^{\beta_0 + \beta_1 \text{Dropsize}_i + \beta_2 \text{Volatility}_i}} \quad (3)$$

or, in logit form:

$$\ln\left(\frac{P(\text{Recovery}_{i,n})}{1- P(\text{Recovery}_{i,n})}\right) = \beta_0 + \beta_1 \text{Dropsize}_i + \beta_2 \text{Volatility}_i \quad (4)$$

where:

$P(\text{Recovery}_{i,n})$ is the probability of recovery of stock i in the n-th year

Dropsize_i is the percentage of the decline in stock i

Volatility_i is the volatility of returns on stock i during the research period

The Recovery variable is defined as a binary variable with the following criteria:

$$P(\text{Recovery}_{i,n}) = \begin{cases} 1, & Close_{i,n} > Close_{i,t_0} \\ 0, & Close_{i,n} \leq Close_{i,t_0} \end{cases} \quad (5)$$

where:

$Close_{i,n}$ is the closing price of stock i in the n-th year

$Close_{i,t_0}$ is the closing price of stock i in the base year t_0

In this study, Volatility_i is measured using the coefficient of variation (CV), which is defined as the ratio of the standard deviation of returns to the average return during the study period. CV is used as an indicator of volatility because it can provide a standardized measure of risk, making it more suitable for comparing stocks with different return levels. This approach is relevant in the context of falling knife stocks have asymmetric return distributions. Using standard deviation alone can potentially introduce scale bias, especially when average returns differ significantly across stocks after a sharp price decline. By

normalizing dispersion by the average return, CV allows for a more comparable measure of volatility and reflects relative risk.

Mathematically, CV can be calculated using the following formula:

$$\text{volatility}_i = CV_i = \frac{\sigma_i}{\bar{R}_i} \quad (6)$$

where:

σ_i is the standard deviation of stock i's return during the research period

$\bar{R}_i$ is the average return of stock i during the research period

This study acknowledges potential endogeneity and omitted variable bias, as stock recovery may also be affected by firm fundamentals and broader market conditions that are not explicitly modeled. Given the price-based focus of this study, the analysis is limited to market-derived variables. Accordingly, the findings should be interpreted as indicating associations rather than strict causal relationships.

This study uses the bootstrapping method to improve parameter estimation accuracy and ensure the stability of the results. This technique involves resampling with replacements from the original dataset to form a distribution of logistic regression parameter estimates, so the estimates will be more stable and unbiased. Furthermore, when traditional assumptions are not fully satisfied, the resulting statistical inference becomes more reliable. Bootstrapping is also an effective technique for estimating confidence intervals and odds ratios, which are important indicators in logistic regression. We implement bootstrapping with 1000 iterations to produce a distribution of logistic regression coefficients.

Research Hypothesis

This study tests the hypothesis that the magnitude of the price decline and return volatility influences the probability of stock recovery in three years after a sharp decline, which is formulated as follows:

$$H_0 : \beta_1 \geq 0 \, , \beta_2 \geq 0$$

(Dropsize and volatility have no effect or have a positive effect on the probability of stock recovery)

$$H_a : \beta_1 < 0 \, , \beta_2 < 0$$

(Dropsize and volatility have a negative effect on the probability of stock recovery.)

The null hypothesis will be rejected if the p-value is less than 0.05.

Goodness-of-Fit

To assess the quality of the logistic regression model, the author uses one of the goodness-of-fit methods, namely the area under the ROC (Receiver Operating Characteristics) curve. The ROC curve itself is a curve that describes the relationship between the true positive rate (TPR/sensitivity) and the false positive rate (FPR/1-specificity) for all possible cut points. The area under the ROC curve (AUC) is valued at 0.5 to 1 and is used to evaluate model performance, with the following interpretation (Çorbacıoğlu & Aksel, 2023):

AUC = 0.5: The model has no discrimination ability (no better than random guessing).

$0.7 \leq AUC < 0.8$: The model has acceptable performance in distinguishing stock recovery categories.

$AUC \geq 0.8$: The model has excellent performance in classifying stock recovery probabilities.

4. RESULT AND DISCUSSION

Descriptive Analysis

The following is the number of stocks evaluated in this study and the number of stocks that fall into the falling knife category. On average, the number of falling knife stocks on the Indonesia Stock Exchange tends to be small, with only 3.32% of stocks falling into the category of falling knife.

Table 2

The Number of Falling Knives

Base year	Total stocks	Falling knives	Percentage
2010	355	5	1.41%
2011	374	1	0.27%
2012	401	6	1.50%
2013	424	8	1.89%

Base year	Total stocks	Falling knives	Percentage
2014	453	6	1.32%
2015	477	38	7.97%
2016	495	8	1.62%
2017	510	17	3.33%
2018	546	21	3.85%
2019	603	44	7.30%
2020	658	40	6.08%
	Average		**3.32%**

Source: Summarized by author

Based on Table 2, 194 falling knife observations were identified from 2010 to 2020. Most of these falling knife stocks are stocks with small market capitalization‡, and stocks with medium market capitalization§, as shown in Figure 1. Low liquidity can cause small-cap and mid-cap stocks to have higher volatility than large market capitalization stocks (Kulshrestha & Bhaduri, 2019). When liquidity is limited, small transactions can trigger larger price changes, giving stocks higher volatility. In addition, Salisu et al. (2018) found that small-cap and mid-cap stocks are generally more sensitive to external shocks than big-cap stocks. Investor behavior is also one of the factors that can cause high volatility in small-cap stocks compared to big-caps (Chakraborty & Subramaniam, 2020; Jena et al., 2021). When there is pressure on the market, small-cap and mid-cap stocks experience a sharper decline because investors tend to switch to big-cap stocks, which are considered to have lower risk. This investor behavior will increase selling pressure, which will ultimately increase volatility.

‡ Small market capitalization is a stock valued below IDR 500 billion.
§ Mid-market capitalization stocks have a market capitalization value between IDR 500 billion and IDR 10 trillion.

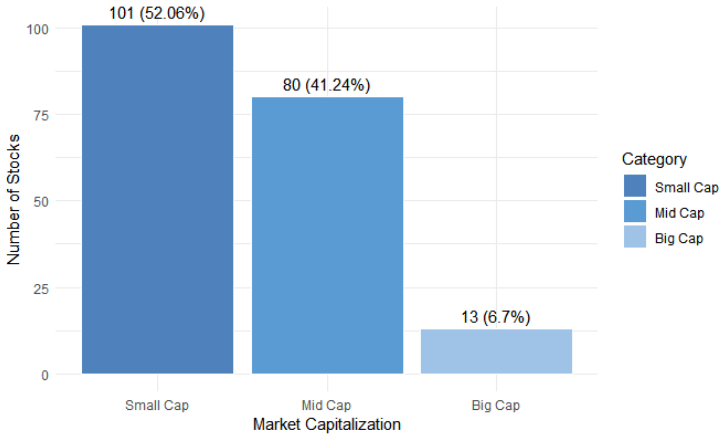

Figure 1

Falling Knives by Market Capitalization Distribution

The characteristics of falling knife stocks in this study can also be seen based on the IPO year group in Figure 2, which consists of stocks that conducted IPOs before 2000, from 2000 to 2009, and from 2010 to 2020. The analysis results show that the stocks that fell the most were those that conducted IPOs from 2010 to 2020, namely, 88 out of 194 falling knife stocks.

The high number of falling knife stocks in the 2010-2020 IPO group can be explained by several factors, one of which is the overvalued condition of the stocks at the time of the IPO. Investors tend to overestimate their ability to predict the success of an IPO, leading to speculative bidding behavior that can further amplify price movements (Min, 2022). IPOs often experience price rationalization; overvalued stocks will experience a price decline until they reach their intrinsic value, leading to a significant price decline after the IPO (Haggard & Xi, 2017). In addition, newly listed stocks often do not have enough historical data for investors to assess. Such situations can lead to speculative behavior, where investors react to news or market trends, thereby increasing volatility (Kuvvet & Palkar, 2019).

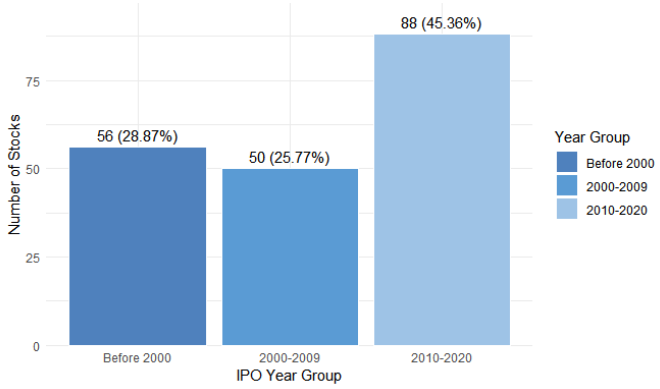

Figure 2

Falling Knives by IPO Year Group

Figure 3 shows the distribution of stocks by sector, where the energy sector is the most dominant, covering 40 stocks or 20.62% of the total, followed by the consumer cyclical sector and properties and real estate. Fluctuations in oil prices are one of the factors that can cause the energy sector to become the sector with the most falling knife stocks. Research shows that oil price volatility significantly impacts the stock prices of energy companies (Dutta, 2018). In addition, the COVID-19 pandemic has had an impact on energy demand, which has caused a significant decline in energy sector stocks during that period (Hasan et al., 2021).

The consumer cyclical and properties and real estate sectors are also vulnerable to the falling knife phenomenon. In the consumer cyclical sector, sensitivity to the economic cycle is one of the leading causes. In addition, earnings volatility can also be a factor in stocks in this sector becoming falling knife stocks. Research by Fitriani and Yanuarta (2022) shows that profitability and earnings volatility significantly affect a company's capital structure. These findings indicate that earnings fluctuations can increase risk perceptions among investors. When earnings reports fall short of expectations or economic indicators show a slowdown, investors react, causing a sharp decline in stock prices.

On the other hand, the property and real estate sectors are vulnerable to the falling knife phenomenon due to their sensitivity to interest rates and economic conditions. Changes in interest rates can significantly affect property values and the profitability of investments in this sector. For example, during an economic

recession, demand for property often decreases, leading to a decline in property prices.

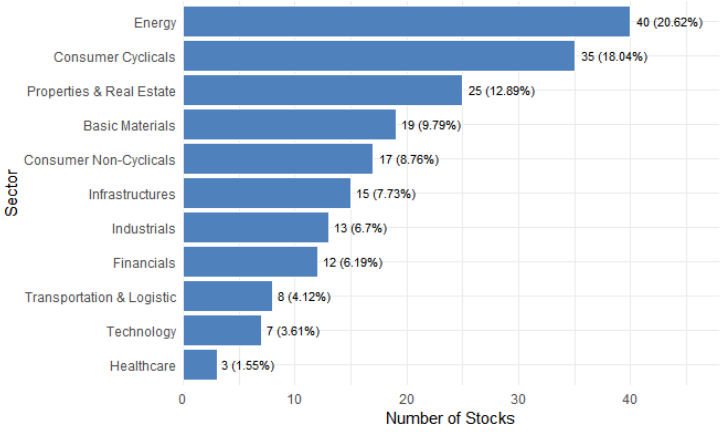

Figure 3

Falling Knives by Sector

Figure 4 shows the average return of falling knife stocks based on the base year and the performance in the following three years. One of the findings of this study is the significant fluctuation in the average return, which varies between base years. In the base years 2010, 2015, 2018, and 2019, the average return in the first, second, and third years shows a positive value, indicating the potential for price recovery in falling knife stocks. Meanwhile, for stocks in the base years of 2011, 2012, 2016, and 2017, the average return is negative, indicating the failure of falling knife stocks to recover.

On the other hand, stocks in the base years 2013, 2014, and 2020 show a different recovery pattern from other years. The average return of falling knife stocks in 2013 and 2014 has a pattern that tends to be stagnant and low, indicating that the stocks did not experience a significant recovery. Meanwhile, the average return of falling knife stocks in 2020 was also low, indicating a weak recovery. Macroeconomic factors, such as the global economic slowdown, market fluctuations, or weak company fundamentals, could cause this. The return pattern seen in Figure 4 also indicates that the performance of falling knife stocks is highly dependent on the context of the base year, including market conditions at that time.

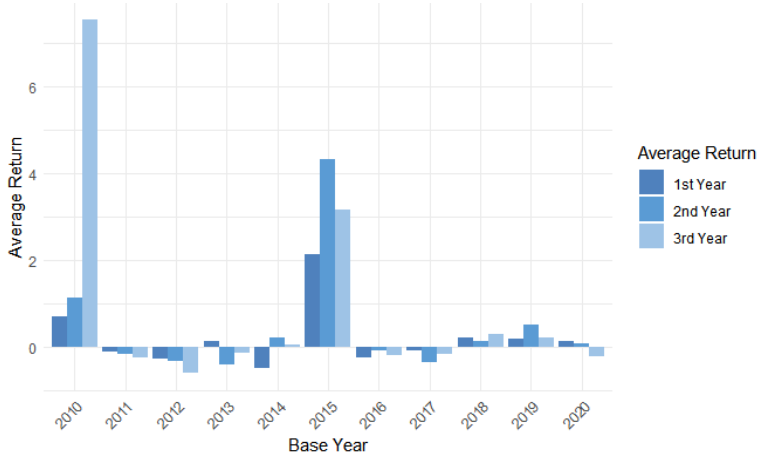

Figure 4

Average Return of Falling Knives

Figure 5 shows the average returns of falling knife stocks from various sectors over the three years after experiencing a sharp decline. The basic material sector generally recorded the most significant recovery, as seen by its high average return compared to other sectors. This finding indicates that stocks in this sector tend to recover faster after a period of sharp decline due to the importance of this industry to the economy (Bouri et al., 2021; He et al., 2020). The energy sector also showed a positive recovery, although it was not as high as the basic material sector. The recovery in the energy sector can be attributed to fluctuations in energy prices, which often experience a rebound after economic uncertainty (Amoako et al., 2022). In contrast, the consumer non-cyclical, technology, and financial sectors recorded relatively low, even negative, returns. This finding indicates that some sectors take longer to recover after a sharp price decline.

Another pattern that can be seen in Figure 5 is the downward trend in the average return from the first, second, and third year in most sectors. This evidence indicates that stock price recovery tends to be more significant after a sharp price decline in the early years. When stock prices fall sharply, investors often view the decline as an opportunity to buy at a lower price, so demand increases. Literature supports this condition by demonstrating that stocks typically undergo price reversals following a crisis (Indrayono, 2021).

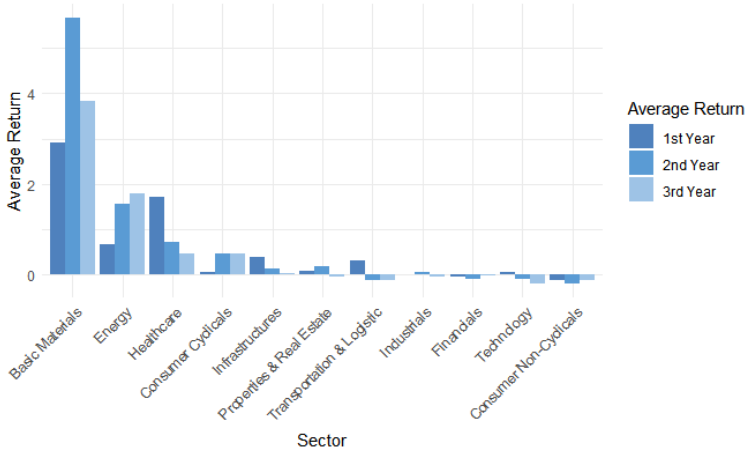

Figure 5

Average Return of Falling Knives by Sector

The performance of falling knife stocks can also be evaluated by calculating the number of stocks with positive returns in the first, second, and third years. Of the 194 falling knife stocks from 2010 to 2020, only 44 stocks (22.7%) had positive returns in all years. This graph indicates the low number of stocks that can recover after experiencing a sharp price decline. Figure 6 also emphasizes the risks associated with investing in falling knife stocks because these stocks are likely to have poor performance, and stock prices could even fall deeper in the following years.

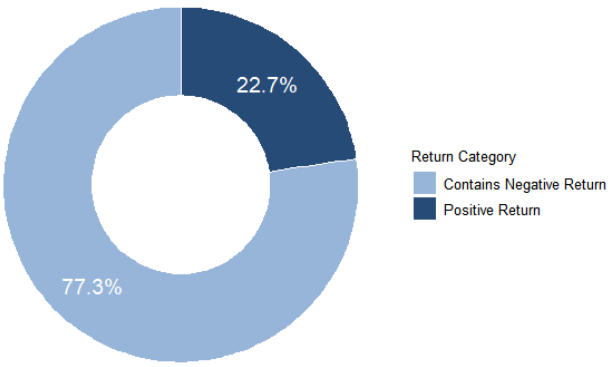

Figure 6

Falling Knives Performance

Figure 7 shows the stocks that have the most positive returns in all years, namely, stocks in the energy sector, with 14 stocks. Stocks in the basic material sector have seven stocks, all with positive returns, followed by the consumer cyclical and properties and real estate sectors with six stocks. Meanwhile, the consumer non-cyclical, industrial, transportation, and logistics sectors have only one positive stock each.

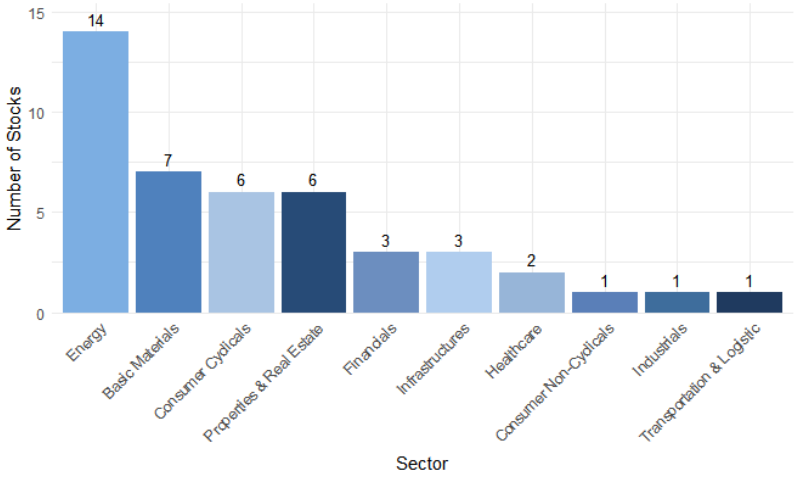

Figure 7

Number of Stocks with Positive Returns by Sector

The descriptive findings outlined above provide a general overview of the characteristics of falling knife stocks. However, to better understand the factors in determining whether a stock will recover or not, a quantitative approach is needed. Therefore, an empirical analysis includes visual exploration and logistic regression to examine two main variables, volatility and magnitude of price decline, on the probability of stock recovery.

Empirical Analysis

Before conducting the logistic regression analysis, an initial exploration was conducted using boxplots to understand the relationship between volatility and the magnitude of price decline on the probability of recovery within one to three years after experiencing a sharp fall.

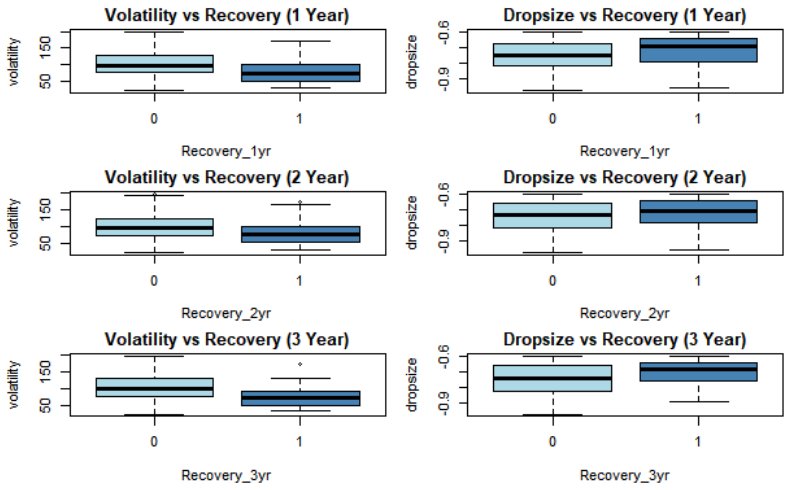

Figure 8

Boxplot of Volatility and Recovery

In the year after the decline, stocks that do not recover are more volatile than those that do (see Figure 8). Conversely, stocks that recover have lower volatility. We also observe a similar pattern in volatility in the second and third years, where stocks with lower volatility are more likely to recover. In terms of dropsize, stocks that recover in one year generally have a smaller price drop than those that do not recover. We also observe a similar pattern in the second and third years, with the differences between the groups diminishing over time.

These findings indicate that the impact of the decline's magnitude on recovery tends to be stronger in the early years after the fall. At the same time, in the longer term, other factors, such as volatility, play a greater role in determining recovery. These exploratory results suggest that while the magnitude of price decline may play a role in short-term recovery, volatility appears to be a more persistent determinant of recovery across longer horizons. The results obtained from this boxplot provide an initial indication of the relationship between the two variables and the possibility of stock recovery to strengthen the logistic regression analysis that will be conducted in the next stage.

The Results of Logistic Regression

The following are the results of logistic regression to see the variables that affect the probability of stock recovery in the first year, second year, and third year.

Table 3

Estimation Result of Logistic Regression

First Year						
Variable	**Original β**	**Bootstrap Bias**	**Lower CI (95%)**	**Upper CI (95%)**	**Odds Ratio**	**P-value**
Constant	2.3751	0.0304				
Dropsize	0.8185	0.0016	-3.0839	4.6573	2.2671	0.6446
Volatility	-0.0220	-0.0004	-0.0344	-0.0127	0.9782	0.0000
Second Year						
Variable	**Original β**	**Bootstrap Bias**	**Lower CI (95%)**	**Upper CI (95%)**	**Odds Ratio**	**P-value**
Constant	0.4017	-0.0528				
Dropsize	-1.1270	-0.1388	-5.1690	2.5760	0.3240	0.5380
Volatility	-0.0198	-0.0007	-0.0330	-0.0100	0.9804	0.0000
Third Year						
Variable	**Original β**	**Bootstrap Bias**	**Lower CI (95%)**	**Upper CI (95%)**	**Odds Ratio**	**P-value**
Constant	2.4302	0.0767				
Dropsize	1.0698	-0.0316	-3.5290	5.2950	2.9148	0.6920
Volatility	-0.0275	-0.0014	-0.0439	-0.0159	0.9728	0.0000

The logistic regression results in Table 3 show that the volatility variable has a statistically significant negative coefficient (p-value < 0.05) in all analysis periods, namely in the first, second, and third years. In addition, the odds ratio (OR) obtained has a value smaller than 1 in all research periods. The results indicate that volatility has a negative effect on the probability of stock recovery. The higher the volatility, the less likely the stock is to return to its pre-fall price, and vice versa. On the other hand, the magnitude of price decline (dropsize variable) does not show statistical significance, which means that it does not directly affect the chance of stock recovery in the three years after the price decline.

Magnitude of Price Decline and Stock Recovery

Although extreme price drops are often followed by partial rebounds, the evidences suggests that the size of the initial decline does not significantly affect the probability of recovery over a three-year horizon. Insights from behavioral

finance can help explain this finding. Large price declines can trigger investor overreaction and temporary mispricing, but these effects appear to be short-term. For example, Zakamulin (2024) shows that extreme negative returns are frequently followed by short-term reversals driven by behavioral responses. Yet these reversals rarely translate into sustained recoveries. Similarly, Guo et al. (2024) documented that extreme loss events tend to produce only partial rebounds, even in the immediate aftermath of the decline. In other words, the market may react quickly, but it does not necessarily fully recover.

Choi (2021) showed that deeper drawdowns are typically associated with longer recovery periods. This pattern suggests that severe price declines may reflect more persistent valuation damage rather than temporary overshooting. Such evidence helps explain why dropsize alone does not reliably predict medium-term recovery probability.

Choi and Jayaraman (2009) argue that post-decline price reversals can arise from liquidity effects and information asymmetry, rather than improvements in fundamentals. When this happens, early rebounds mainly reflect temporary trading dynamics instead of true value correction. As a result, the apparent recovery following sharp declines may be misleading.

Taken together, these findings suggest that while the magnitude of a price decline captures the severity of the initial drop, it says relatively little about what happens afterward. Factors such as post-crash market conditions, investor confidence, and firm resilience appear to matter far more for sustained recovery. Simply put, a big fall does not automatically imply a meaningful recovery.

Return Volatility and Stock Recovery

Unlike dropsize, volatility is consistently a significant determinant of recovery probability. High volatility signals ongoing uncertainty and heightened risk, which often make investors more cautious. As a result, capital inflows slow down, and price stabilization tends to take longer.

This finding is consistent with previous studies that suggest that high volatility is often associated with greater market uncertainty, thus hindering stock recovery (Hamal & Gautam, 2021; Just & Echaust, 2020; Liu & Zhang, 2015;

Rakshit & Neog, 2021; Zhao, 2023). When volatility increases, investors tend to be more cautious in making investment decisions, which leads to greater selling pressure and reduces the likelihood of stock price recovery. Moreover, Kongsilp and Mateus (2017) demonstrated that volatility risk significantly predicts future returns during crisis periods, reinforcing the role of volatility as a proxy for market-wide uncertainty.

From a market microstructure perspective, higher anticipated volatility increases inventory risk faced by liquidity providers, reducing their willingness to supply liquidity and slowing price adjustment (Bogousslavsky et al., 2025). This mechanism provides a plausible explanation for why highly volatile falling knife stocks struggle to recover even several years after the initial decline.

Based on the research results, volatility is a factor that needs to be considered in assessing the potential for stock recovery. Stocks with low volatility are more likely to recover than stocks with high volatility. In addition, policies are needed to increase information transparency and strengthen investor protection to reduce the negative impact of extreme price declines.

Goodness-of-Fit

To assess the quality of the logistic regression model, the author uses one of the goodness-of-fit methods, namely the area under the ROC (Receiver Operating Characteristics) curve.

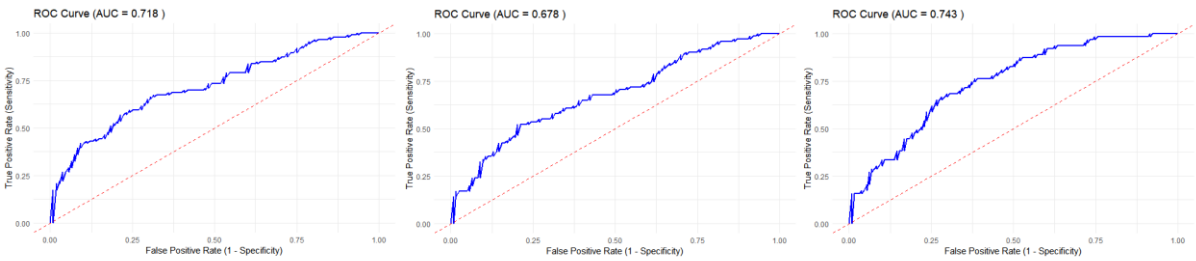

Figure 9

ROC Curve (AUC)

Figure 9 shows that the logistic regression model has an AUC ranging from 0.7 to 0.8, indicating that the model has acceptable predictive ability in distinguishing stocks that can recover from those that cannot. This result indicates that volatility is important in assessing the likelihood of stock recovery. In addition, the model used has a fairly good level of accuracy for prediction purposes.

5. CONCLUSION AND SUGGESTIONS

Conclusion

This study shows that volatility negatively and significantly affects the likelihood of stock recovery after a sharp decline. The higher the volatility of a stock, the smaller the chance of it returning to its pre-decline price. Conversely, lower-volatility stocks tend to have a greater chance of recovering within a specific period. These data shows that volatility is an important factor that investors need to pay attention to when dealing with stocks that are under pressure.

Unlike volatility, the magnitude of price decline variable does not significantly affect stock recovery in the three years after the drop. Despite a sharp decline in stock prices, the stock's ability to recover does not directly correlate with the size of the price drop. This finding reminds investors to focus more on volatility factors than just the size of price drops when evaluating stocks that have the potential to recover.

We found through descriptive analysis that small-cap and mid-cap stocks generally have higher volatility than big-cap stocks. This finding indicates that market capitalization also plays a role in influencing price recovery. In terms of sectors, stocks from specific sectors, such as consumer cyclicals, properties, and real estate are more vulnerable to the falling knife phenomenon because both are highly influenced by economic cycles and interest rate changes. In contrast, sectors such as basic materials and energy tend to recover faster, as reflected by the high average return compared to other sectors. Meanwhile, the consumer non-cyclical, technology, and financial sectors take longer to recover, some of which even record negative returns.

Interestingly, the performance of stock recovery also heavily depends on the context of the time of the event. When macroeconomic conditions are relatively stable or even improving, the chances of falling knife stocks recovering to their original price levels tend to be greater. This data indicates that market momentum and investment timing are crucial factors that should not be ignored.

Only about 22.7% of the 194 falling knife stocks showed consistent positive returns after the decline. This finding confirms that investing in stocks that experience sharp declines carries significant risk because most of them can not recover to their previous price levels. In addition, in the analysis of annual volatility, stocks that do not recover within a specific period tend to have higher volatility than those that do. This fact strengthens the empirical finding that low volatility provides better recovery opportunities.

Theoritical Contribution

The findings of this study contribute to the literature on stock behavior after extreme declines. Specifically, the results highlight volatility as a significant price-based determinant of recovery. Unlike prior studies that emphasize average post-decline returns or fundamental screening, this study models stock recovery as a probabilistic outcome. By providing empirical evidence from Indonesia, this study enriches the literature with insights from an emerging market context, where recovery mechanisms may differ from those documented in developed markets.

Practical Implication

From a practical perspective, the results suggest that investors should not rely solely on the magnitude of price declines when evaluating stocks. Instead, volatility provides a more informative signal of recovery potential. Falling knife stocks with relatively low volatility are more likely to recover than highly volatile ones.

Sectoral differences also indicate that recovery prospects vary across industries, highlighting the importance of sector-specific risk assessment. For policymakers, improving information transparency and strengthening investor protection mechanisms may help reduce uncertainty following extreme price declines.

Limitations

This study has several limitations. The analysis is still limited to two main variables, return volatility and the magnitude of price decline, so it has not considered other factors that can also affect stock recovery. Factors such as market sentiment, fundamental company performance, or the role of government policy intervention have not been included in the model. In addition, the analysis of sectors and market capitalization size is still descriptive and has not been tested using a regression approach.

Further Research

For further research, expanding the scope of the study is important. Adding fundamental and macroeconomic variables or using other approaches can provide a deeper understanding of stock recovery patterns. In addition, cross-country studies should be considered to compare market characteristics in various regions. Therefore, future research will offer investors and policymakers a more comprehensive and applicable picture.

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