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Original Article

Predicting the Stock Price using Historical Price, Volatility and Downside Risks

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Abstract: This study examines and analyses the influence of historical stock prices, volatility risk, and downside risk on stock prices in the rapidly growing Infrastructure sector on the Indonesian Stock Exchange (IDX) from 2014 to 2022. Using a nine-year dataset, we integrated standard deviation and Ulcer Index as volatility and downside risk measures, respectively, employing Structural Equation Modeling (SEM). Results show a significant positive effect of historical stock prices on future prices in this dynamic market. However, this positive trend is counteracted by the negative effect of volatility risk on stock prices, emphasising the importance of risk management strategies in the Infrastructure sector. We have also identified a positive effect for historical volatility risk (t) on future volatility risk (t+1), indicating a potential connection between past and future market volatility. Also, downside risk is established as a negative effect on stock prices, emphasising risk mitigation in historical stock performance. In addition to indirect effects, we found that historical stock price (t) plays a mediating role, affirming the influence of downside risk (t) on future stock price (t+1). This research provides valuable insights into predicting future stock prices, offering a comprehensive understanding of the interplay among historical performance, volatility, and downside risk. These findings contribute to developing effective strategies for investors and policymakers to navigate the complexities of the stock market.

Keywords: Stock price; Volatility risk; Downside risk

1. Introduction

Predicting stock prices is crucial for academic research, business, and investor applications. Volatility, a long-recognised element influencing stock prices, plays a vital role in market prediction and has been studied for decades. While accurate prediction is challenging, analysing volatility as a risk indicator offers a potential avenue. Investors must understand how volatility risk operates and its impact on financial markets for effective portfolio selection strategies (Markowitz, 1952). In addition to volatility, another risk measure to consider is downside risk, which refers to the potential loss or decrease in the value of an investment below a certain threshold. Both volatility and downside risk are based on numerical data that can be

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employed as input for predicting the stock market (Lei, 2018). The stock price reflects much information, and analysing the hidden historical data can be used for the prediction of stock market trends, e.g., Chen et al. (2021), Luo et al. (2021) and Huang et al. (2022). While the efficient market hypothesis posits that past prices do not impact future movements, empirical studies challenge its accuracy (Zhou et al., 2020; Zhang et al., 2024; Gil-Alana et al., 2018). Investors can still make predictions using indicators like realised volatility; analysing past volatility patterns enables insights into potential future market conditions. This knowledge is crucial for financial decision-making, aiding risk management and asset allocation, and enhancing preparation and adaptation to varying market conditions (Liu & Pan, 2020).

Previous research in the financial market field often used standard deviation (Borochin & Zhao, 2019, Tsafack et al., 2023; Liu & Zhang, 2021) and the Ulcer Index (Jaroonchokanan et al., 2022; Freitas & Bertini, 2023), each partially, as measures of volatility risk and downside risk, respectively. Although both these types of risk have been extensively analysed in the literature, there is limited research that has combined both of them to analyse their effects on stock prices. Therefore, this research combines both to obtain a more comprehensive picture of how volatility and downside risks affect future stock prices. In addition to volatility, the historical price can be used to predict the direction of stock price movements. However, it may only be effective in the short term and inconsistent in the long term (Chudziak, 2023). Therefore, this study utilises quarterly data to capture more robust and reliable trends over an extended period, aiming to provide a comprehensive analysis of stock price movements in the rapidly growing Infrastructure sector on the IDX from 2014 to 2022. By employing a quarterly approach, the research addresses the limitations associated with short-term analyses and enhances the reliability of predictions concerning future stock prices. This timeframe allows for a more thorough examination of market dynamics, considering both bull and bear market conditions and capturing the impact of significant events, such as the post-2008 financial crisis and the COVID-19 pandemic.

Both risk measures are rooted in the historical movements of stock prices. A technical indicator emerges as a prominent tool for forecasting future stock prices by utilising historical data and risk assessments. This indicator stands out as one of the most popular sources of information for predicting the stock market (Bustos & Pomares-Quimbaya, 2020). As we delve into the intricate relationship among historical price trends, volatility risk, downside risk, and the application of technical indicators, a comprehensive understanding of their collective impact on predicting future stock prices emerges. In line with the research conducted by Liu & Pan (2020), which found that past volatility is a good predictor during economic expansion phases, this study focuses on the stock index of Indonesia's rapidly growing Infrastructure sector. The objective is to examine how historical stock price volatility may influence the prices of IDX Infrastructure Index stocks. Based on data from Statista (2023), Indonesia's infrastructure budget experienced a significant increase from 157.4 trillion IDR to 394.1 trillion IDR in 2019, representing a growth of 150.38% over 5 years. After 2020, the figures consistently remained above 300 trillion IDR. This trend aligns with President Joko Widodo's policy focus on the infrastructure sector since the beginning of his presidency.

Therefore, this study aims to comprehensively understand the influence of historical stock prices, volatility, and downside risks on the Infrastructure sector. In observing the substantial infrastructure development over the last decade, this research seeks to provide valuable insights into the intricate dynamics of stock movements within the IDX's infrastructure sector, offering a comprehensive perspective amid the booming development in Indonesia.

2. Literature Review

Several previous studies have separately examined the impact of stock price in the past period, volatility risk and downside risk on stock price movements, whether that impact is direct or indirect. Mohrschladt (2021) found that ordering historical stock returns significantly predicts the cross-section of subsequent returns. Dixit & Soni (2023) conclude that historical data specifically the movements in stock prices, plays a pivotal role in developing a reliable stock market prediction model, as evidenced by the positive outcomes and accurate forecasting achieved through the proposed methodology. Wang et al. (2023) emphasised the critical role of understanding the historical price trends, demonstrating that incorporating this comprehensive historical information leads to more precise stock price predictions, aligning with signalling theory (Spence, 1974), which posits that entities, including the stock market, use observable signals to convey otherwise unobservable information, influencing perceptions and actions. This alignment suggests that the market employs historical data as a communicative tool to anticipate and respond to future stock movements, emphasising the importance of historical information as a valuable signalling tool in understanding and forecasting stock market dynamics. In light of these insights, the following hypothesis is formulated:

H1: Historical stock price (t) significantly affects future stock price (t+1).

Vasudevan (2023) observed that investors tend to become more inclined to sell their stocks as stock volatility increases. However, it is important to note that this behaviour alone may not definitively indicate that stock prices will decrease. The relationship between stock volatility and price movement is complex and influenced by various factors, including market sentiment, investor perceptions, and economic conditions. Further research is needed to investigate whether the increased selling pressure from higher volatility could lead to decreased stock prices. Market dynamics are multifaceted, and a deeper analysis is necessary to draw more conclusive conclusions.

Gong et al. (2022) found that stock volatility risk influences investor sentiment, but whether this impact results in negative or possibly even positive sentiment has not been definitively concluded. Therefore, this research delves further into the effects on stock prices. Additionally, it discovers that stock volatility exhibits heterogeneous characteristics across various industries, meaning that stock volatility risk varies among different industry sectors. Furthermore, in this research, we specifically investigate these effects within Indonesia's infrastructure sector. Saraf & Kayal (2023) use beta and variance to assess whether they can forecast future stock returns. They conclude that the predictability of beta and variance about stock returns depends on the time frame. This study shows that the predictability holds for medium-to-long-term time horizons (7 years and 5 years on a rolling basis) but not for short-term periods (3 years and an ultra-short period of 6 months). Traub (2019) found that volatility affects stock market returns, and this relationship is negative, which means that when volatility increases, stock market returns tend to decrease, and vice versa. For instance, high volatility can create uncertainty in the market and make investors more cautious, reducing stock market returns. In consideration of these insights, we propose the following hypotheses:

H2a: Volatility risk has a significant effect on stock price.

H2b: Historical Volatility risk (t) significantly affects the future stock price (t+1).

In alignment with Xie et al. (2019) notion that risk in the past can be utilised to predict future risk, we further propose:

H2c: Historical Volatility risk (t) significantly affects the Volatility risk in the subsequent period (t+1).

These hypotheses collectively aim to explore the intricate relationships between volatility, historical volatility, and their respective impacts on stock prices over time. In addition to the issue of volatility risk, several studies have examined the effects of downside risk in stock market dynamics. Ergun (2019) found that a portfolio with a high level of extreme downside risk yields a higher average realised return than a portfolio with low extreme downside risk, which is statistically significant. Luo et al. (2021) document that earnings downside risk (accounting-based downside risk) contains information on firms' future operating performance and is positively associated with expected stock returns in Chinese stock markets, and the return predictability of earning downside risk mainly comes from its accrual downside risk component. Ali (2019) found that downside risk plays a substantial role in asset pricing. Also, the research underscores that downside risk remains a significant factor influencing the creation of successful trading strategies. Xie et al. (2019) found that downside risk can be used to predict future downside risk (Xie et al., 2019). Considering the research findings above that highlight the significance of downside risk as a valuable factor in financial contexts, we propose the following hypotheses to analyse:

H3a: Downside risk has an effect on stock price (in the same period)

H3b: Downside risk (t) has a significant effect on the future stock price (t+1)

Moreover, in exploring the potential mediating role of historical stock price and future volatility risk, the following hypotheses are posited:

H4: Historical stock price (t) mediates the effect of downside risk (t) on future stock price (t+1)

H5: Future volatility risk (t+1) mediates the effect of historical volatility risk (t) on future stock price (t+1)

3. Materials and Methods

The data in this study consists of IDX Infrastructure Index Stocks Prices. Secondary data sources are obtained from investing.com for 9 years, from 2 January 2014 to 30 December 2022. The selected time frame aims to enable the observation of stock price fluctuations during specific market movements, including the post-2008 financial crisis and the period of the COVID-19 pandemic starting in March 2020. Additionally, a 9-year duration may encompass both bear and bull market conditions. The standard risk measures used in this study include standard deviation (or σ) to measure volatility and the Ulcer Index to measure downside risk. This study utilises a quantitative research approach to examine and analyse the predictability of stock prices. The primary emphasis is on evaluating how historical stock price, volatility, and downside risk influence the (forecasting of future) stock prices. Regarding variables and their measurements, the dependent variable is represented by the (future) stock price (for the next quarter [t+1]). On the independent side, historical price is scrutinised by examining the previous stock price during the period (t), specifically the previous quarter. Also, volatility risk is measured using the standard deviation, serving as a proxy for (historical) volatility risk. In addition, downside risk is assessed by utilising the Ulcer

Index as a proxy for downside risk. The Ulcer Index is the square root of the mean square of the percentage drawdown from the preceding maximum price within the specified (t) period. We employ Structural Equation Modelling (SEM) through SmartPLS 4.0 software to analyse these variables and their interrelations. This statistical method allows for a comprehensive exploration of the relationships between the identified variables, providing a robust framework for understanding the intricate dynamics influencing (future) stock prices, Figure 1 below is the model:

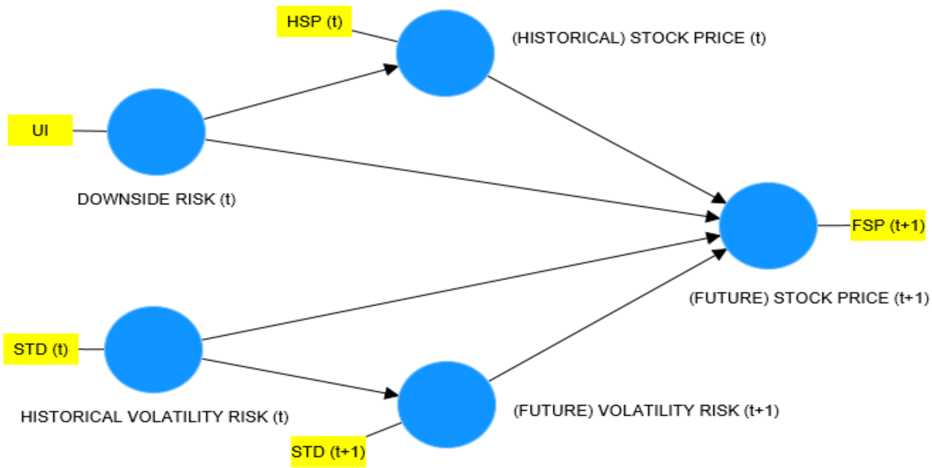

Figure 1. Research framework

4. Results

Table 1 summarises the results obtained from hypothesis testing, offering a comprehensive overview of the study's key findings and their implications. The summary table below provides a concise overview of the results obtained from hypothesis testing, presenting key findings and their implications. This summary guides assessing direct and indirect effects on future stock prices based on historical stock prices, volatility risk, and downside risk.

Table 1. Hypothesis Testing Summary

Hypothesised Path		Coefficients	Sig.	Conclusion
Direct effect				
H1	Historical Stock Price (T) -> Future Stock Price (T+1)	0.696	0.000	Accepted
H2a	Volatility Risk (T+1) -> Stock Price (T+1)	-0.356	0.010	Accepted
H2b	Historical Volatility Risk (T) -> Future Stock Price (T+1)	-0.035	0.811	Rejected
H2c	Historical Volatility Risk (T) -> Future Volatility Risk (T+1)	0.491	0.041	Accepted
H3a	Downside Risk (T) -> Stock Price (T)	-0.487	0.000	Accepted
H3b	Downside Risk (T) -> Future Stock Price (T+1)	-0.074	0,583	Rejected
Indirect Effect				
H4	Downside Risk (T) -> Historical Stock Price (T) -> Future Stock Price (T+1)	-0.339	0.001	Accepted

Hypothesised Path		Coefficients	Sig.	Conclusion
H5	Historical Volatility Risk (T) -> Future Volatility Risk (T+1) -> Future Stock Price (T+1)	-0.175	0.124	Rejected

The primary objective of this study was to explore the intricate dynamics influencing the predictability of (future) stock prices. The empirical analyses of the data revealed significant insights into the multifaceted relationships among historical stock prices, volatility, and downside risk, providing valuable contributions to the evolving understanding of market dynamics. In this section, we delve into the detailed analysis of the hypotheses, exploring the coefficients and p-values derived from the statistical tests conducted. The hypotheses are structured to evaluate the direct and indirect effects of historical stock price, volatility risk, and downside risk on (future) stock prices.

Table 1 shows the coefficient of 0.696 with a p-value of 0.000, providing robust evidence that supports the acceptance of H1. This signifies a significant positive relationship between historical stock prices (t) and future stock prices (t+1). The findings align with the existing literature (Mohrschladt, 2021; Dixit & Soni, 2023; Wang et al., 2023), reinforcing the notion that historical stock prices play a pivotal role in predicting subsequent stock movements. Contrary to initial expectations, the immediate impact of volatility risk (H2a) is negative, with a coefficient of -0.356 (p = 0.010), challenging the conventional belief that higher volatility predicts lower stock prices. However, historical volatility risk's direct impact (H2b) is statistically insignificant (p = 0.811), suggesting that past volatility might not reliably predict immediate future stock movements. Also, the effect of historical volatility risk on future volatility risk (H2c) is significant (coefficient: 0.491, p = 0.041). This suggests that although historical volatility risk may not directly predict immediate stock price movements, it does influence future volatility. This implies that while historical volatility risk might not directly impact future stock prices, its influence is observed through the continuity of volatility over time. These nuanced findings contribute to the ongoing discourse on the temporal aspects of volatility and its role in shaping future market conditions.

The findings highlight the intricate dynamics between historical stock prices and volatility risk influencing future stock prices. The rejection or acceptance of hypotheses contributes valuable insights into the complexities of these relationships, providing a foundation for further research and practical implications in the field of stock market analysis. Also, the negative coefficient of -0.487 (p = 0.000) for the direct effect of downside risk on stock prices in the same period (t) (H3a) highlights its substantial impact on historical market trends. However, the non-significant impact of downside risk on immediate future stock prices (H3b) with a coefficient of -0.074 (p = 0.583) suggests that downside risk might not be an immediate predictor of market movements in the next period. This distinction emphasises the importance of contextualising downside risk within a broader context when evaluating its potential influence on future stock prices. The influence of downside risk on stock prices in the same period (t) but not for predicting future stock prices (t+1) gives insight into how downside risk contributes to understanding the dynamics within a specific timeframe. This observation suggests that downside risk may significantly influence stock prices in the same period, but its utility in predicting immediate future stock prices is limited. This nuanced finding underscores the need for a comprehensive analysis considering the temporal aspects of downside risk when evaluating its implications on future market conditions.

H4 and H5: Indirect Effects of Downside Risk and Historical Volatility Risk on Future Stock Prices

The significant negative coefficient of -0.339 (p = 0.001) for the indirect effect of downside risk on future stock prices through historical stock prices (H4) indicates that historical trends mediate downside risk's impact. It aligns with the notion that a comprehensive downside risk analysis necessitates understanding its influence within the broader historical narrative. Conversely, the non-significant indirect effect of historical volatility risk on future stock prices through future volatility risk (H5) (coefficient: -0.175, p = 0.124) suggests that the continuity of volatility might not be a dominant predictor of future stock prices. This result underscores the necessity for a more in-depth exploration of the temporal dimensions of volatility in shaping future market conditions. In light of these results, it becomes imperative to delve deeper into the intricate dynamics of volatility and its temporal dimensions. This exploration should focus on uncovering additional factors that may contribute to the unpredictability of future stock prices, considering that the continuity of volatility alone may not fully capture the complexity of market behaviour. Further research could examine the interplay of various market indicators and external factors, offering a more comprehensive understanding of how volatility influences stock prices over time.

The two hypotheses above (H4 and H5) provide insight that the future stock price (t+1) is more influenced by historical downside risk (t) than historical volatility risk (t), indicating that the dynamic stock market is more susceptible to changes that may lead to stock price declines than to historical volatility fluctuations. It suggests that the downside risk of the stock price from the previous period has a more significant impact on future stock prices than historical volatility risk. This finding offers insights to stock market investors to pay closer attention to the risk of stock price declines as a factor that may influence their investment decisions. It highlights the importance of considering the dynamics of this specific risk in their portfolio strategies. These comprehensive findings contribute to the evolving understanding of market dynamics, urging researchers and investors to consider the temporal dimensions and broader historical context when formulating predictive models. The results underscore the intricate relationships between historical stock prices, volatility, downside risk, and their collective impact on predicting future stock prices in the context of the rapidly growing Infrastructure sector in Indonesia.

5. Conclusions

The comprehensive findings from this study provide valuable insights into the complex dynamics influencing the (predictability of future) stock prices in the rapidly growing Infrastructure sector on the Indonesian Stock Exchange (IDX). This study confirms the significant positive influence of historical stock prices on future stock prices, aligning with established literature. It emphasises the enduring role of past movements in predicting subsequent stock movements. Despite rejecting the hypothesis that historical volatility risk (t) directly impacts future stock price, the influence of volatility risk (t) on stock price in the same period persists. Additionally, the accepted hypothesis (H2c) indicates a significant impact of historical volatility risk (t) on future volatility risk (t+1). It underscores the complexity of volatility's effects, suggesting that while historical volatility may not directly predict future stock prices, it plays a role in influencing future volatility dynamics. Downside risk plays a substantial role in shaping stock prices in the same period, but its immediate impact on future stock prices is not statistically significant. The importance of considering downside risk within a broader historical context is emphasised.

This study emphasises the mediating role of historical stock prices in shaping the effect of downside risk on future stock prices. Conversely, the mediating effect of future volatility risk in the impact of historical volatility risk on future stock prices is not supported. In conclusion, these findings contribute to a more comprehensive understanding of market dynamics in the Infrastructure sector on the IDX. Researchers and investors are encouraged to consider the temporal dimensions and broader historical context when formulating predictive models, recognising the nuanced relationships between historical stock prices, volatility, downside risk, and their collective impact on predicting (future) stock prices. The findings have substantial implications for various stakeholders, shedding light on critical market dynamics and decision-making aspects. This study contributes to an enriched understanding of market dynamics, particularly in the rapidly growing Indonesian Stock Exchange (IDX) infrastructure sector. By exploring the interplay among historical stock prices, volatility, and downside risk, the research provides valuable insights for academics, practitioners, and policymakers.

The research highlights the enduring role of historical stock prices in predicting future movements. Investors and decision-makers can leverage this insight to make informed choices, recognising the significance of past market behaviour in shaping future outcomes. In summary, the implications of this study extend beyond academic discourse, offering practical insights for investors, policymakers, and researchers involved in the Infrastructure sector on the IDX. The nuanced understanding of historical data, volatility, and downside risk contributes to a more comprehensive and strategic approach to market analysis and decision-making. Several recommendations emerge to enrich our understanding of market dynamics and enhance the accuracy of predicting (future) stock prices. Firstly, extending the study duration beyond the current nine years could provide a more robust understanding of long-term trends and the impact of significant events. Also, cross-sectoral analyses may unveil sector-specific dynamics, offering a more nuanced view of stock price movements. Exploring the influence of macroeconomic factors, such as government policies or global economic trends, can further enrich the predictive models. Integrating advanced machine learning techniques and big data analytics could enhance the accuracy of predictions, offering more sophisticated insights into market behaviour. Qualitative research methods like interviews or surveys may complement quantitative analyses by capturing market sentiments and investor perceptions.

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