Utilizing Asymmetric Shock on Volatility and Asymmetric Beta for Enhanced Investment Strategies in the Stock Exchange of Thailand

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การใช้ปัจจัยของระดับความผันผวนแบบไม่สมมาตร (asymmetric shock) และเบต้าแบบไม่สมมาตร (asymmetric beta) เพื่อเสริมสร้างกลยุทธ์การลงทุนในตลาดหลักทรัพย์แห่งประเทศไทย

นายณัฐพล ศิรินคร

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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ณัฐพล ศิรินคร : การใช้ปัจจัยของระดับความผันผวนแบบไม่สมมาตร (asymmetric shock) และเบต้าแบบไม่สมมาตร (asymmetric beta) เพื่อเสริมสร้างกลยุทธ์การลงทุนในตลาดหลักทรัพย์แห่งประเทศไทย. (Utilizing Asymmetric Shock on Volatility and Asymmetric Beta for Enhanced Investment Strategies in the Stock Exchange of Thailand) อ.ที่ปรึกษาหลัก : ดร.ธนวิต แซ่ซือ

การศึกษานี้สำรวจผลกระทบของความไม่สมมาตรในความผันผวนและค่าเบต้าภายในตลาดหลักทรัพย์ของไทย พบว่าพอร์ตการลงทุนที่ประกอบไปด้วยหุ้นที่แสดงความไวต่อการสั่นคลอนทางลบที่ต่ำและการตอบสนองต่อแนวโน้มของตลาดที่สูงมีผลการดำเนินงานที่ดีกว่าในสภาวะตลาดต่างๆ การวิเคราะห์ข้อมูลตั้งแต่ปี 2018 ถึง 2022 เน้นย้ำถึงประโยชน์ของการบูรณาการความไม่สมมาตรเข้ากับกลยุทธ์การลงทุน โดยเฉพาะกลยุทธ์ลงทุนแบบ Long-Short ถูกพิจารณาว่ามีประสิทธิภาพสูง ซึ่งเป็นวิธีที่จะเอาชนะความไม่สมมาตรนี้ การเปรียบเทียบพอร์ตการลงทุนที่อิงกับความไม่สมมาตรกับพอร์ตการลงทุนแบบดั้งเดิมและดัชนี SET ยังเพิ่มเติมให้เห็นถึงข้อได้เปรียบของกลยุทธ์เหล่านี้ในการเพิ่มผลตอบแทนที่ปรับเทียบกับความเสี่ยงและการจัดการความเสี่ยงทางด้านลบได้อย่างมีประสิทธิภาพ ทำให้นักลงทุนมีข้อได้เปรียบที่สำคัญในการจัดการพอร์ตการลงทุน.

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Nuttapol Sirinakorn : Utilizing Asymmetric Shock on Volatility and Asymmetric Beta for Enhanced Investment Strategies in the Stock Exchange of Thailand. Advisor: TANAWIT SAE SUE, Ph.D.

This study investigates the impacts of asymmetric shock on volatility and beta within the Thai stock exchange. It finds that portfolios composed of stocks that demonstrate lower sensitivity to negative shocks and heightened responsiveness to market trends consistently outperform in various market conditions. The empirical analysis, spanning from 2018 to 2022, underscores the benefits of integrating asymmetry into investment strategies. A long-short strategy, in particular, is identified as highly effective, providing a means to capitalize on this asymmetry. The comparison of asymmetry-based portfolios with traditional ones and the SET index further illuminates the advantages of such strategies in enhancing risk-adjusted returns and effectively managing downside risk, thus offering investors a significant advantage in portfolio management.

Field of Study:	Finance	Student's Signature ....
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TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

CHAPTER 1 : INTRODUCTION

1.1 Background and significance of the problem

Stock markets are characterized by inherent uncertainty, reflected in both short and long-term price movements. Despite being undesirable for investors, this uncertainty is an unavoidable aspect of choosing the stock market as an investment avenue.

In the world of finance and investment, risk has become an integral part of modern economies, with volatility and uncertainty being inherent characteristics of stock markets. Managing and understanding risk is crucial for successful portfolio management. Volatility and beta are key measures used to assess and quantify market risk. While conventional approaches assume constant volatility and beta, previous study has revealed the presence of asymmetries in these measures, indicating that their behavior may vary across different market conditions(Huang, Liu et al. 2012)

The concept of "asymmetric shock on volatility" refers to the unequal impact of unexpected events or shocks on the level and behavior of volatility in the stock market. It recognizes that positive and negative shocks have distinct effects on volatility, and that volatility exhibits different characteristics depending on prevailing market conditions.

Positive shocks refer to unexpected events or news that have a positive impact on the market, such as favorable economic indicators or corporate announcements. These positive shocks typically lead to a temporary increase in market volatility, reflecting heightened excitement or optimism among investors.

Conversely, negative shocks encompass adverse events, such as economic downturns, geopolitical tensions, or negative company news. Negative shocks often result in more substantial and prolonged increases in market volatility, signaling higher levels of uncertainty, fear, and risk aversion among investors.

The asymmetric impact of shocks on volatility implies that negative shocks have a more pronounced effect on volatility compared to positive shocks of the same magnitude. Negative shocks tend to elicit stronger market reactions, resulting in larger and more persistent increases in volatility.

Understanding the asymmetric impact of shocks on volatility is crucial for effective risk management and informed investment decision-making. By recognizing how different types of shocks affect volatility, investors can assess the potential risks associated with specific events and adjust their strategies accordingly. This knowledge enables them to be more responsive to market dynamics, make well-informed investment choices, and align their actions with their risk tolerance and investment objectives.

Volatility forecasting models are commonly used by investors and financial institutions to estimate and predict future volatility. Some of the commonly employed models include the exponentially weighted moving average (EWMA), autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH) models (Ayele, Gabreyohannes et al. 2017)

Among these models, GARCH models are widely considered superior in volatility forecasting. They take into account the past variance of the stock market index and capture the volatility clustering phenomenon, where periods of high volatility tend to be followed by more periods of high volatility. This makes GARCH models particularly suitable for capturing the asymmetry of volatility. (Kayahan and Memis 2014)

Numerous studies support the use of GARCH models in stock market volatility forecasting, highlighting their ability to capture the impact of shocks on volatility and provide accurate predictions. By employing these models, investors can gain insights into the potential magnitude and direction of future volatility, which can inform their risk management strategies and investment decisions.

Similarly, the concept of "asymmetry of beta" challenges the assumption that beta values remain constant across all market conditions. Previous research has shown that beta values may differ significantly between bull and bear market phases (Longin and Solnik 2001), implying that the relationship between a stock's risk and the overall market's movements may be asymmetrical. Recognizing and exploiting these asymmetries can enable investors to develop more robust investment strategies and enhance risk-adjusted returns. (Ang and Chen 2002), find that the correlation between the equity portfolio and the market is much greater for downside moves than for upside moves. (Ang, Chen et al. 2006), define downside (upside) beta to characterize stocks with high sensitivity to downside (upside) market movements. In the cross section of firms, they show that downside risk will positively predict a firm's future returns because investors who are sensitive to downside losses require a premium for holding assets with higher downside beta. Despite this appealing asset pricing property of downside risk at cross-sectional level, there has been little empirical research into how downside risk or asymmetry between downside and upside risk are priced in the aggregate market return.

Further research is needed to thoroughly examine the presence and characteristics of an asymmetric relationship between stock price movements and market movements. Previous studies have produced mixed and weak findings regarding beta changes during different market phases, indicating the necessity for a more nuanced approach. To address these limitations, this research proposes an adjusted methodology that incorporates a predetermined threshold and a smooth linear transformation function.

The refined methodology moves beyond binary classifications of market phases and recognizes the inherent asymmetry in market movements. By introducing a threshold-based classification, the research acknowledges that market movements exhibit distinct characteristics based on their magnitude and direction. This allows for a more accurate representation of the underlying asymmetry in stock price movements relative to the overall market. Additionally, the incorporation of a smooth linear transformation function provides a comprehensive understanding of the market's behavior by considering both the magnitude and direction of movements.

By employing this adjusted methodology, the research aims to contribute to the existing knowledge on the asymmetric shock on volatility and asymmetry of beta. Incorporating the asymmetric shock on volatility and asymmetry of beta in portfolio construction provides valuable advantages for investors, including enhanced risk management, improved risk-adjusted performance, and adaptive portfolio management. By analyzing the asymmetric shocks on volatility, investors gain insights into the uneven impact of unexpected events or shocks on price fluctuations. This understanding allows them to adjust their portfolio allocations accordingly, mitigating risk during periods of heightened volatility driven by specific types of shocks. Similarly, considering the asymmetry of beta allows for the identification of stocks with different sensitivities to market movements, reducing downside risk and increasing portfolio resilience. Diversification plays a crucial role in mitigating idiosyncratic risk, and constructing a well-diversified portfolio with a sufficient number of stocks can effectively reduce idiosyncratic risk and enhance risk-adjusted performance.

Moreover, this approach improves risk-adjusted performance by aligning portfolios with the risk-return dynamics of the market and capitalizing on stocks with favorable asymmetrical profiles. Adaptive portfolio management, driven by monitoring market conditions and making timely adjustments, enables investors to capitalize on evolving risk-return dynamics, potentially outperforming passive indexing strategies. By incorporating the asymmetric shock on volatility and asymmetry of beta, investors can construct portfolios that are well-suited to market conditions, optimizing risk-return trade-offs and achieving greater resilience and performance.

Aiming to explore the utilization of the asymmetric shock on volatility and asymmetry of beta for investment strategies, this research endeavors to shed light on previously unexplored aspects of market dynamics. By providing investors with a more comprehensive framework for decision-making, this research aims to empower them to capitalize on opportunities and effectively manage the risks associated with market asymmetry. By incorporating these asymmetries into portfolio management and optimization techniques, investors can potentially enhance risk management, capitalize on market inefficiencies, and improve the overall performance of their investment portfolios.

To accomplish this objective, we will review relevant literature on the topic, examining studies that have investigated the asymmetry of volatility and beta in various market conditions. We will also analyze different methodologies and models proposed for capturing and exploiting these asymmetries effectively.

Furthermore, empirical analysis will be conducted using real-world market data to validate the presence and significance of asymmetries in shock on volatility and beta. Recognizing and utilizing the asymmetry of shock on volatility and asymmetry of beta can offer investors a unique perspective on market risk and returns. By going beyond traditional linear assumptions, investors can gain a competitive edge in portfolio management, achieving improved risk-adjusted performance. The findings from this research will provide valuable insights into the practical implications of incorporating asymmetry into investment strategies.

1.2 Objective

The research aims to explore the utilization of the asymmetric shock on volatility and asymmetry of beta for investment strategies and investigate the presence and characteristics of the asymmetric shock on volatility and asymmetry of beta in the stock exchange of Thailand. The research focuses on dividing the Thai stock market into two main periods, the market upturn period and the market downturn period. It aims to analyze the presence and characteristics of asymmetric shock on volatility and asymmetry of beta during these distinct market conditions. By analyzing the historical data and employing empirical studies, the research seeks to provide insights into how the asymmetric shock on volatility and asymmetry of beta can be utilized in investment strategies within the Thai stock exchange. It aims to uncover any patterns, differences, or specific characteristics exhibited by these measures during the identified market upturn and downturn periods. The findings of the research are expected to contribute to a better understanding of the dynamics and implications of asymmetric shock on volatility and asymmetry of beta in the Thai stock market. They may offer insights into the potential benefits and limitations of incorporating these measures into investment strategies during different market conditions. This knowledge can help investors in Thailand make more informed decisions, improve risk management techniques, and potentially enhance their investment performance. Additionally, the research aims to develop innovative portfolio construction strategies that incorporate advanced risk management techniques, taking into account the asymmetrical nature of volatility and beta. These strategies are designed to mitigate downside risk while maximizing potential returns, offering investors a framework aligned with their risk preferences and financial goals within the context of the stock exchange of Thailand. Furthermore, the research will evaluate the performance of asymmetry-based portfolios by comparing them to traditional portfolios and the benchmark SET index. Various performance metrics, such as risk-adjusted returns, excess returns, and downside protection, will be assessed to determine the effectiveness of the asymmetry-based approach in outperforming the market and achieving superior risk-adjusted performance. The findings will provide valuable insights into the practical implications and potential benefits of incorporating asymmetry into portfolio management strategies specifically tailored to the stock exchange of Thailand.

In summary, the aims of the study are:

1. To investigate the asymmetric shock on volatility and asymmetry of beta
2. To develop effective portfolio construction strategies and evaluate the performance of asymmetry-based portfolios in different market conditions, such as the market upturn and downturn periods

1.3 Research Hypothesis

Hypothesis 1.a: The shock on volatility of stock returns in the stock exchange of Thailand exhibits asymmetry, with different levels and patterns of volatility during periods of market upturn or stability compared to periods of market downturn or instability.

Hypothesis 1.b: The beta values of stocks in the stock exchange of Thailand display asymmetry, indicating that the sensitivity of stock returns to overall market movements differs between bull and bear market phases.

Some studies find evidence in favor of asymmetric models, such as EGARCH, for the case of exchange rates and stock returns predictions. Examples include (Cao and Tsay 1992), (Kat and Heynen 1994), (Loudon, Watt et al. 2000) and (Pagan and Schwert 1990). Other studies find evidence in favor of the GJR-GARCH model. (Granger and Poon 2001) for the case of stock returns volatility. Moonis and Shah (Citation 2003) estimated the time varying beta using individual stocks of NSE 50 and found that for 52% of the stocks the existence of time varying beta is not rejected. Their study examined only the beta constancy for a particular time period and not the stability of beta in different market conditions. Moreover, in contrast to Moonis and Shah's paper an endogenous continuous time varying model is deployed, which allows for a smooth transition between the regimes.

Given the nature of the Thai stock market, which involves various types of market participants such as retail investors, domestic institutions, and foreign institutions, there is a potential for asymmetric information, Behavioral biases and market panic sell-offs. These factors can contribute to a significant level of asymmetry in volatility and beta. Therefore, we expect that the magnitude of asymmetry in the Thai stock market would be notably positive and larger compared to previous studies conducted in other markets. The unique dynamics and characteristics of the Thai stock market can amplify the impact of these factors, leading to more pronounced the asymmetric shock on volatility and asymmetry of beta

Hypothesis 2a: During the period from 2018 to 2020-Q1 (market downturns), portfolio with less sensitivity to negative shock and more sensitivity to market movements is expected to outperform other portfolios in terms of cumulative returns over this period.

Hypothesis 2b: During the period from 2020-Q2 to 2022 (market upturns), portfolio with less sensitivity to negative shock and more sensitivity to market movements is expected to outperform other portfolios in terms of cumulative returns over this period.

Hypothesis 2c: over a 5-year period, the portfolio's performance relative to downside risk, as measured by comparing the RoMaD (Return over Maximum Drawdown), portfolio with less sensitivity to negative shock and more sensitivity to market movements is expected to be significantly higher than other portfolios.

The asymmetry of shock on volatility and asymmetry of beta have received significant attention in academic research due to its influence on risk management strategies and optimal portfolio choices. Studies such as (Longin and Solnik 2001) have demonstrated that the correlation between asset returns and the aggregate market return is stronger in downside markets compared to upside markets. Similarly, (Ang, Chen et al. 2006) have found that the correlation between equity portfolios and the market is greater for downside moves than for upside moves.

To mitigate the potential losses associated with market downturns and ensure participation in market upturns, the investment strategy we aim to focus on is selecting stocks with the least sensitivity to negative shock and more sensitivity to overall market movements. By employing a double-sort strategy, we aim to create a robust selection process that considers both the overall stock risk, represented by volatility, and the market risk, measured by beta. Diversification during the portfolio formation further helps mitigate idiosyncratic risk. This approach enables us to construct a portfolio that minimizes exposure to market fluctuations while maintaining the potential to rally with the market during upturns.

Additionally, by incorporating the Return on Maximum Drawdown (RoMaD) metric, we can evaluate the portfolio's ability to recover from losses. A higher RoMaD indicates that the portfolio has the potential to generate better returns relative to the magnitude of its worst loss. This provides further confidence that the portfolio is designed to withstand adverse market conditions and recover more efficiently.

CHAPTER 2 : LITERATURE REVIEW

2.1 Asymmetric Shock on Volatility

There are two prominent theories that aim to explain the asymmetry of volatility. The first theory, known as the leverage effect, was proposed by (Black 1976). According to this explanation, when a company's stock price declines, its equity value also decreases, resulting in an increased debt-to-equity ratio or leverage. Higher leverage is generally associated with increased riskiness, and greater risk is linked to higher volatility.

In an effort to test Black's hypothesis, (Christie 1982) conducts an analysis across different firms. He examines the relationship between the debt-to-equity ratios of companies and the asymmetry of their stock price volatility. While he discovers a strong correlation between asymmetry and leverage, he concludes that leverage alone is insufficient to explain the asymmetric effects.

An alternative explanation for the asymmetry in stock price volatility is referred to as the volatility feedback hypothesis, proposed by (Campbell and Hentschel 1992). According to this hypothesis, the causality runs from volatility to price: positive shocks to volatility increase future risk premia, and if future dividends remain constant, the stock price should decline.

Campbell and Hentschel find supporting evidence for their hypothesis, but they also observe that the leverage effect contributes to the asymmetric behavior of stock market volatility. It should be noted that these two hypotheses are not mutually exclusive, and both effects may be present in the data. Recent advancements in the literature on asymmetric volatility are discussed in (Bekaert and Wu 2000).

A number of studies have established the effectiveness of the GARCH model in estimating the conditional volatility of time series for forecasting purposes (Abdalla and Winker 2012), (Nikmanesh and Nor 2016). Specifically, the exponential GARCH (EGARCH) and GARCH (1,1) models have demonstrated superior performance compared to other univariate GARCH models.

(Chong, Ahmad et al. 1999) conducted a study on the forecasting performance of various GARCH models, including GARCH, GARCH-M, EGARCH, and

IGARCH, using Malaysia's Composite Index, Tins Index, Finance Index, Properties Index, and Plantations Index from 1989 to 1990. Their findings indicated that EGARCH outperformed other models in out-of-sample forecasting and in describing index skewness. In contrast, the IGARCH model performed poorly.

(Gabriel 2012) examined the forecasting ability of the threshold GARCH (TGARCH) model for the Romanian stock index (BET Index) and concluded that it was the best model for this purpose. However, (Lupu, Lupu et al. 2007) argued that EGARCH was more effective in forecasting the volatility of the Romanian Composite Index (BET-C). (Miron and Tudor 2010) supported this view by demonstrating a higher accuracy level of EGARCH in estimating Romania's daily returns compared to TGARCH and power GARCH (PGARCH) models.

On the other hand, (Frimpong and Oteng-Abayie 2006) found that the GARCH (1,1) model, assuming a normal distribution, outperformed the random walk, EGARCH, and TGARCH models when applied to the Databank Stock Index. (Al Rahahleh and Kao 2018) validated the efficiency of the standard GARCH model in estimating the volatility of the Saudi stock market. The advantages of the GARCH model over other forecasting models are mainly attributed to its ease of estimation and the availability of diagnostic tests (Drakos, Kouretas et al. 2010) .

Furthermore, (Sharma, Aggarwal et al. 2021) found that the standard GARCH model performed well in capturing stochastic dependencies and was more robust than advanced GARCH models in one-step-ahead forecasts. (Liu and Hung 2010) conducted a comparative study analyzing the performance of different GARCH models (GARCH-N, GARCH-t, GARCH-SGT, and GARCH-HT) along with EGARCH and GJR-GARCH. They concluded that the GJR-GARCH model produced the most accurate forecasts, while the EGARCH model ranked second.

2.2 Asymmetry of beta

A substantial body of empirical studies has provided validation for the usefulness of the Capital Asset Pricing Model (CAPM) ((Jensen, Black et al. 1972), (Fama and French 2003). Despite some criticisms, the model continues to be regarded as theoretically robust and serves as a benchmark for empirical investigations in finance. According to the CAPM, only systematic risk is rewarded, as unsystematic risk can be mitigated through diversification. The expected return of a risky security is determined by adding the risk-free rate to the risk premium, which is estimated using beta. This interrelationship between risk and return also enables testing of their association.

The original study by (Fama and MacBeth 1973) employed a three-step approach to establish the validity of CAPM. Firstly, they estimated betas for individual securities. Secondly, they estimated portfolio betas for a subsequent period, and finally, they regressed portfolio returns on portfolio betas. Analyzing monthly data from 1935 to 1968, they discovered a positive relationship between returns and beta, leading them to conclude that the model adequately describes the risk-return relationship in capital markets.

However, some studies ((Schwert 1983) and (Reinganum 1981) found weak evidence in support of beta and suggested that the relationship between returns and beta could be spurious. The differences in returns across numerous portfolios were not significant, and the relationship was inconsistent across different sub-periods. The effectiveness of beta as the primary measure of systematic risk for individual securities was challenged by (Chen 1982), who proposed the use of various macroeconomic variables such as industrial production risk premium, yield curve dynamics, inflation, consumption, and oil prices. (Fabozzi and Francis 1979) examined beta in the context of mutual funds and concluded that it reacts differently in bull and bear market conditions.

Other studies (Wiggins 1992), (Bhardwaj and Brooks 1993) and (Howton and Peterson 1998) explored portfolio returns using the dual-beta approach introduced by (Fabozzi and Francis 1977). (Wiggins 1992) observed that the dual-beta model improved return predictions by considering factors like size, past beta, and historical portfolio return performance. (Bhardwaj and Brooks 1993) found that "small firm stocks underperform large firm stocks when beta risk is allowed to vary in bull and bear markets. Some studies (Lakonishok and Shapiro 1984) and (Fama and French 1992) reported insignificant evidence between beta and average returns. (Fama and French 1992) even concluded that the CAPM model does not adequately explain average stock returns over the past 50 years. These studies investigated the ability of various market variables to explain cross-sectional stock returns, with market value of equity and book-to-market ratio demonstrating the most significant effects on returns. However, contrasting viewpoints argued that the beta measures in the model specified by (Fama and French 1992) were mis-specified. Conversely, (Howton and Peterson 1998) found a significant size effect and demonstrated that beta could explain cross-sectional returns effectively.

Another set of studies focused on establishing a conditional relationship between returns and beta. (Pettengill, Sundaram et al. 1995) proposed that when realized market returns exceed the risk-free rate, portfolio betas should exhibit a positive relationship, whereas when realized market returns fall below the risk-free rate, beta and returns should display an inverse relationship. In order to address situations where realized excess returns are not always positive, argued that while the CAPM model postulated a positive relationship between beta and expected returns, empirical investigations (Fama and French 1992) used realized returns instead of expected returns. By analyzing US market data, they found a significant relationship between conditional beta and returns. In a more recent study, (Durand, Lim et al. 2011) tested the modified CAPM proposed by (Pettengill, Sundaram et al. 1995) in eleven emerging markets and discovered supporting evidence for a positive estimated risk premium in up-market conditions and a negative estimated risk premium in down-market conditions.

Several studies, including (Ang, Chen et al. 2006) and (Levi and Welch 2020), have demonstrated that the utilization of downside beta can lead to the generation of positive alpha.

However, recent research has provided new insights that may help resolve the ongoing controversy. (Levi and Welch 2020) have discovered that asymmetry of beta actually diminishes the performance of hedging and risk-pricing models, even when accounting for Fama French factors. These findings offer valuable perspectives for reconsidering the effectiveness of asymmetry of beta in various financial applications.

CHAPTER 3 : DATA

The data used in this study was collected from reliable sources to ensure the accuracy and reliability of the research findings. The primary data sources for the study were the daily closing stock prices for both the SET100 and sSET indexes, which represent a comprehensive range of firms traded on the Stock Exchange of Thailand (SET).

The SET100 index consists of the top 100 companies listed on the SET based on market capitalization and liquidity. These stocks are considered to be representative of the broader market and provide valuable insights into the performance of large-cap companies in Thailand.

In addition to the SET100 index, the sSET index was included as a supplementary data source. The sSET index covers a broader range of companies, including small-cap stocks, and aims to reflect a larger segment of the Thai stock market. By incorporating the sSET index into the data collection process, the study captures a more comprehensive representation of the market and includes a wider array of companies.

The inclusion of both the SET100 and sSET indexes in the data collection process allows for a more holistic analysis of the Thai stock market. By considering a broader range of companies, including both large-cap and small-cap stocks, the study gains a more complete understanding of market dynamics, investor sentiment, and overall market performance.

To obtain the daily closing stock prices, the study utilized reputable sources such as SETSMART (SET Market Analysis and Reporting Tools) and the Bloomberg database. These sources are widely recognized for providing accurate and up-to-date information on stock prices and market data.

In addition to the stock price data, the study also required information on the risk-free rate. To determine the risk-free rate, the secondary market rate for the Thailand 1-Year Bond Yield, without seasonal adjustment, was used as a proxy. The Thai Bond Market Association's official website (https://www.thaibma.or.th) was the source for obtaining this information for the corresponding period.

By utilizing these comprehensive and credible data sources, the study aims to ensure the accuracy and reliability of the research findings. The data collection process spanned from January 2018 to December 2022, covering a substantial period of 5 years. This extended time frame allows for a comprehensive analysis of the SET100 and sSET index's historical performance and the behavior of the included companies.

From **Figure 1** The research primarily emphasizes a comprehensive analysis of the Thai stock market, encompassing a significant historical period. Instead of dissecting the market into distinct short-run phases, such as the market upturn period (2020Q2-2022) and the market downturn period (2018-2020Q1), the study adopts a holistic long-run perspective spanning from 2018 to 2022.

This approach allows for a more thorough exploration of how asymmetric shocks, portfolio behaviors, and risk-adjusted returns evolve and interact over a broader timeframe. By considering the entire period, the research aims to capture overarching trends, persistent patterns, and the cumulative impact of various factors on the Thai stock market's dynamics.

Analyzing the market as a continuous long-run period provides a more comprehensive view of how investor sentiments, economic conditions, and other macroeconomic variables influence market behavior and portfolio performance over time. It enables a deeper understanding of the market's resilience, adaptability, and response to external shocks and internal dynamics.

By adopting this long-run perspective, the research strives to offer valuable insights that extend beyond short-term market fluctuations and contribute to a more enduring understanding of the Thai stock market's characteristics and investment strategies.

Figure 1 the historical periods of upturn and downturn markets in the selected timeframe (2018 -2022).

https://www.tradingview.com

CHAPTER 4 : METHODOLOGY

4.1. Portfolio construction

Constructing asymmetry-based strategies in portfolio construction using only past performance entails utilizing historical data to identify stocks or assets with favorable characteristics in terms of asymmetry in volatility and beta. To implement this approach, the stocks are sorted into nine groups based on their past performance over the previous year. Each group is assigned an equal weight in the portfolio construction process. The asymmetry of volatility is assessed using the GJR-GARCH model, which captures the asymmetric response of volatility to positive and negative shocks. The model helps identify stocks that exhibit a higher sensitivity to negative shocks, indicating a greater potential for downside risk.

Similarly, the asymmetry of beta is evaluated using a smooth linear function, which considers the stock's historical sensitivity to market movements. By incorporating both the asymmetry of volatility and beta, the strategy aims to select stocks that not only demonstrate favorable risk-return characteristics but also exhibit a lower sensitivity to negative shocks and downside market movements.

The portfolio is then reconstructed on a quarterly basis, specifically on January 1st, April 1st, July 1st, and October 1st, to adapt to changing market conditions and incorporate up-to-date information. During the reconstruction process, the weights of each stock within the nine groups using equal weight allocation. This dynamic approach enables continuous optimization of the portfolio's risk-return profile. Equal weight allocation provides an unbiased distribution of investments across stocks, promoting diversification and reducing concentration risk. It avoids overweighting any single stock, preventing it from dominating the portfolio's performance.

The evaluation of the portfolio's performance involves comparing its returns against a market benchmark. The strategy aims to achieve superior returns by selecting stocks with favorable asymmetry in volatility and beta characteristics, indicating the potential for both upside performance and downside risk mitigation. By outperforming the benchmark, the strategy demonstrates its effectiveness in capturing opportunities and managing risk.

4.2 Asymmetric shock on volatility

To forecast the parameter that measures the asymmetry of volatility, we consider the three commonly used models: the EGARCH model by (Nelson 1991), the GJR-GARCH model by (Glosten, Jagannathan et al. 1993).

While there is a wide range of GARCH models available in the literature, this study focuses on a selection of commonly used and relatively successful models, aiming to provide a representative analysis of the asymmetry of volatility. By utilizing the GJR-GARCH model, we aim to capture and quantify the asymmetric behavior of volatility in the stock exchange of Thailand. This model has been widely applied in empirical research to capture the presence of asymmetry in financial time series, and its inclusion in this study allows for a comprehensive investigation of volatility dynamics and the identification of potential asymmetries.

We assume that daily returns are defined as $r_t = \mu + \varepsilon_t$ where $\varepsilon_t = \sigma_t z_t$ and $z_t \sim i.i.d.(0,1)$

GJR-GARCH Model

Glosten, Jagannathan and Runkle (1993) introduced a popular volatility model (GJR- GARCH) that allows for asymmetric effects. The model is an extension of the GARCH model where it is assumed that the parameters of squared residuals depend on the sign of the shock. The main difference from the standard model is an additional variable in the conditional variance equation equal to the product of a dummy variable d_{t-1} and ε_{t-1}.

The general model is of the form (1):

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} \qquad (1)$$

Where γ donates the asymmetric parameter; d_{t-1} donates a dummy variable when $\varepsilon_{t-1} < 0$, $d_{t-1} = 1$ and when $\varepsilon_{t-1} \geq 0$, $d_{t-1} = 0$.

For the GJR model is asymmetric, in that positive and negative shocks of equal magnitude have different effects on conditional volatility. While γ is the differential impact of negative residuals onto immediate volatility persistence. Therefore, asymmetry exists for GJR if:

$$\text{asymmetry for GJR: } \gamma > 0.$$

In this research, the RStudio program was employed to code and estimate the parameters of the GJR-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. The GJR-GARCH model is widely recognized as a valuable tool for effectively modeling and forecasting financial volatility, especially in situations involving asymmetry or skewness in the data.

4.3 Constructing a portfolio using magnitude of asymmetric shock on volatility.

To measure the asymmetric shock on volatility, the GJR-GARCH model is applied to each asset in the portfolio. The estimated γ parameter is then used as a measure of the asset's sensitivity to negative shocks and the asymmetry in its volatility response. A higher and statistically significant value of Gamma γ indicates a greater degree of asymmetry, with negative shocks having a stronger impact on volatility than positive shocks.

Once the γ parameters are obtained for all assets, a ranking can be established based on the magnitude of asymmetry. Assets with higher Gamma γ values are considered to have a higher level of asymmetry and greater sensitivity to negative shocks. These assets may be perceived as riskier in terms of downside volatility.

From **Figure 2** , we can rank the values of Gamma γ in ascending order, representing the degree of asymmetry of volatility, for the pool of stocks under consideration. This ranking allows us to divide the stocks into three groups with equal proportions of approximately 33% in each group.

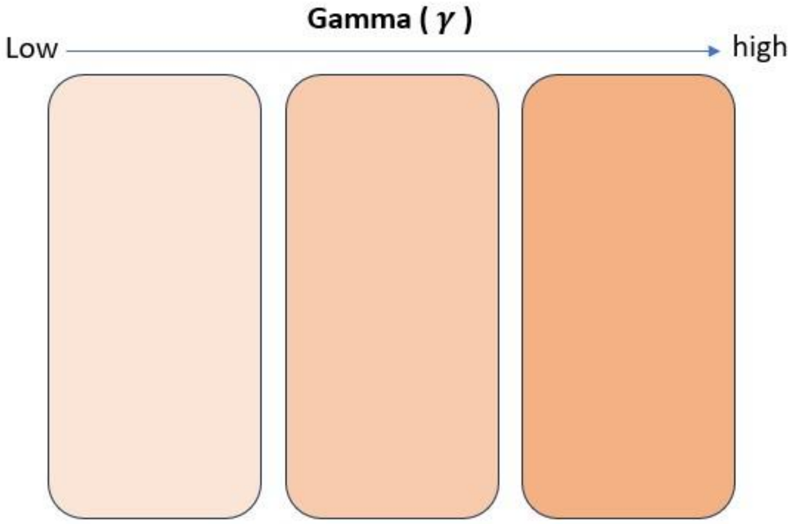
The first group consists of stocks with the lowest values of Gamma γ, indicating lower sensitivity to negative shocks and less asymmetry in volatility. These stocks exhibit a relatively more balanced response to both positive and negative shocks.

The second group comprises stocks with intermediate values of Gamma γ. They exhibit a moderate degree of asymmetry in volatility, indicating a somewhat stronger response to negative shocks compared to positive shocks.

The third group consists of stocks with the highest values of Gamma γ. These stocks demonstrate the highest degree of asymmetry in volatility, with a more pronounced response to negative shocks relative to positive shocks.

By dividing the stocks into these three groups, we create a diversified portfolio that includes stocks with varying levels of sensitivity to negative shocks and asymmetry in volatility. This approach helps manage downside risk and potentially provides a more stable performance during turbulent market conditions.

Figure 2 A pool of stocks can be ranked based on their gamma values



4.4 Asymmetry of beta

We estimated beta of the stocks using the following approaches:

First, the beta value was estimated using simple OLS following Equation (2) which is the most common measure of beta.

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{2}$$

Secondly, we captured the asymmetric nature of beta related to the upward and downward movements of the market using Equation (3). When beta during upward movements (β_{UP}) of the market is higher than the beta during downward movements (β_{DN}), the stock is considered attractive by the investors as it tends to offer high payoffs at the time of the rising market but would fall at a lower rate when the market falls. On the contrary, a stock with higher β_{DN} would be unattractive as it would give a lower return when the market is falling.

$$r_{it} = \alpha_i + \beta_{UPi} r_{mt} + \beta_{DNi} r_{mt} + \varepsilon_{it} \tag{3}$$

The up and down movements of the market can also be captured by adding a variable to the Equation (2) as follows.

$$r_{it} = \alpha_i + \beta_{1i} r_{mt} + \beta_{2i} D_t r_{mt} + \varepsilon_{it} \tag{4}$$

Where D_t will assume a value of +1 when the excess return of the market is nonnegative and −1 when the market return is negative. A positive and significant value of the coefficient β_2 would signify that beta is higher during upward movements of the market compared to the downward trends of the market and vice versa. In this measure, $\beta_{UP} = \beta_1 + \beta_2$ and $\beta_{DN} = \beta_1 - \beta_2$. This is a minor variation from using a dummy variable where the dummy takes two values: 0 and 1.

In the next step, to avoid sharp differentiation of market movements, we used a normalizing measure to capture the degree of market changes, where the magnitude and direction of market movements were transformed between two user-specified values. Supposing that "A" and "B" are the minimum and maximum values of the scale in which the actual values of market return (r_{mt}) would be transformed; the following formula can be used.

$$N_t = A + \frac{(r_{mt} - r_m(Lowest))}{(r_m(Highest) - r_m(Lowest))}(B - A) \tag{5}$$

In the proposed conversion, the highest return during the past years was taken as $r_m(Highest)$ and similarly, the lowest return of past years was taken as $r_m(Lowest)$. We set the value of the lower limit A to −1 and the upper limit B to +1 so that converted values lie between the limits of ±1. The normalization function was, therefore, simplified as follows.

$$N_t = -1 + \frac{(r_{mt} - r_m(Lowest))}{(r_m(Highest) - r_m(Lowest))} \times 2 \tag{6}$$

The following regression was performed to capture the asymmetric influence market movements on the beta coefficient.

$$r_{it} = \alpha_i + \beta_{1i} r_{mt} + \beta_{2i} N_t r_{mt} + \varepsilon_{it} \tag{7}$$

where, N_t measures the state of market movement (both direction and magnitude) estimated using Equation (6). Similar to the earlier approach, β_2 coefficient measures the asymmetric impact of market movements and $\beta_{UP} = \beta_1 + \beta_2$ and $\beta_{DN} = \beta_1 - \beta_2$. A significant value of β_2 would indicate the asymmetric nature of beta even when a smooth linear function was used to capture the state of market movement.

Finally, to find the joint influence of both the indicators (D_t and N_t), the following regression was used.

$$r_{it} = \alpha_i + \beta_{1i} r_{mt} + \beta_{2i} D_t r_{mt} + \beta_{3i} N_t r_{mt} + \varepsilon_{it} \tag{8}$$

From equation (8) where $\beta_{2i} + \beta_{3i}$ represents the coefficient of asymmetry of beta, we can interpret the worst-case scenario as the situation where the market return is at its lowest (bottom) or highest (peak). In this scenario, the combined effect of β_{2i} and β_{3i} captures the stock's sensitivity to both the market direction (β_{2i}) and the magnitude of market movements (β_{3i}).

When the market return is at its lowest, a significant and negative value of $\beta_{2i} + \beta_{3i}$ would indicate that the stock's beta is asymmetrically lower, implying a smaller decrease in the stock's returns compared to the overall market during market downturns. This suggests that the stock has the potential to offer some level of downside protection or resilience during adverse market conditions.

Conversely, when the market return is at its highest, a significant and positive value of β_{2i} + β_{3i} would signify that the stock's beta is asymmetrically higher. This implies that the stock has a higher potential for increased returns compared to the overall market during periods of market upturns, indicating a favorable performance during bullish market conditions.

In our research, we aim to capture the asymmetric nature of beta, considering both the direction and magnitude of market movements. To achieve this, we introduced two indicators: D_t, which captures the market direction, and N_t, which measures the state of market movement using a smooth linear function. In our regression analysis, we included both D_t and N_t as explanatory variables.

The coefficient β_{2i} represents the impact of D_t on the beta coefficient, reflecting the asymmetric influence of market direction on the stock's beta. Similarly, the coefficient β_{3i} quantifies the effect of N_t, which captures the magnitude and smoothness of market movements, on the beta coefficient.

In our analysis, we derive the coefficient of asymmetry of beta by combining β_{2i} and β_{3i}, resulting in what we refer to as the beta differential. This combined coefficient reflects the joint influence of both market direction and the smooth linear measure of market movement on the asymmetry of beta of the stock. This approach provides valuable insights into the stock's behavior during different market conditions and enhances our ability to assess its risk and return characteristics.

4.5 Constructing a portfolio using magnitude of asymmetric shock on volatility and asymmetry of beta.

The measurement of the asymmetry of beta for stocks and the construction of a portfolio involves assessing the degree of sensitivity to market movements and the presence of asymmetry in beta values across different stocks.

To measure the asymmetry of beta, one approach is to estimate the beta coefficient for each stock, which represents the sensitivity of its returns to market movements. A higher beta indicates a higher sensitivity to market fluctuations, while a lower beta suggests a lower sensitivity.

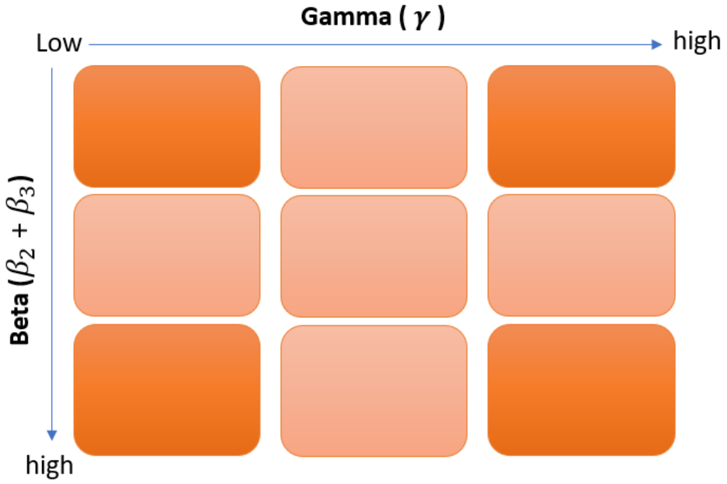
The first group consists of stocks with the lowest value of beta, indicating lower sensitivity to overall market movements. These stocks exhibit a relatively lower level of systematic risk and may be considered less volatile compared to the broader market.

The second group comprises stocks with intermediate values of beta. They exhibit a moderate level of sensitivity to market movements and represent a moderate level of systematic risk.

The third group consists of stocks with the highest values of beta. These stocks demonstrate a higher sensitivity to overall market movements and represent a higher level of systematic risk. They are generally more volatile and have the potential for larger price swings compared to the broader market.

From **Figure 3**, we can observe the ascending order of beta values for the stocks under consideration. This ranking enables us to further divide each of the 3 gamma-ranked stock groups (from step **4.3**) into three groups resulting in the total of nine groups (3-by-3 grid), with each group containing approximately 11% of the stocks from the entire pool. We then construct the portfolios using the stocks the stocks within the same group, creating 9 diversified portfolios that includes stocks with varying levels of sensitivity to negative shocks (asymmetry volatility) and sensitivity to market movements. This portfolio construction approach helps diversify the idiosyncratic risk while maintaining the desirable risk profiles based on asymmetries of volatility and beta, and enables us to investigate whether the chosen risk profiles can potentially improve the risk-adjusted performance of the portfolio.

Figure 3 A pool of stocks can be ranked based on their Gamma and Beta differential.



4.6 Evaluating asymmetry-based strategies in portfolio construction.

To evaluate the performance of the portfolio, we can select four groups of stocks based on the combination of gamma (asymmetry of volatility) and beta (sensitivity to market movements) From **Figure 4**, these groups are as follows:

1) Low Gamma, Low Beta asymmetry: This group consists of stocks with both low gamma values (indicating lower sensitivity to negative shocks and asymmetry in volatility) and low beta differential (indicating relatively lower sensitivity to market movements when market is down as compared to other stocks). These stocks are expected to exhibit relatively stable and less volatile performance compared to the overall market.

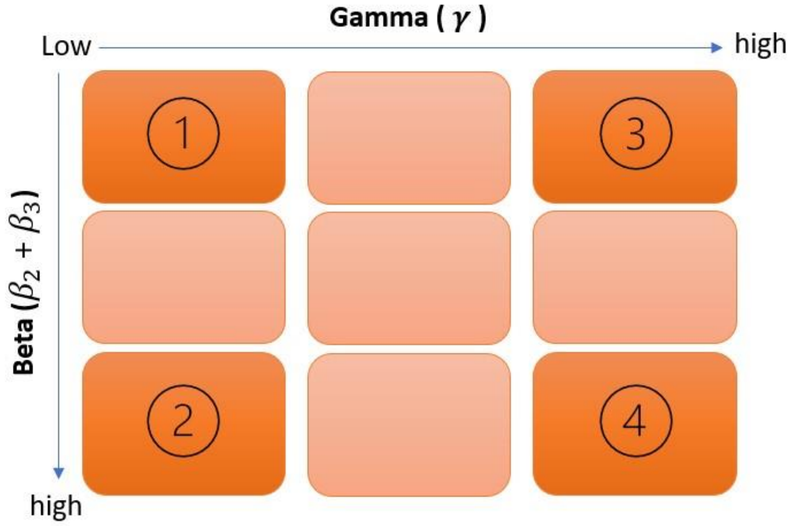
2) Low Gamma, High Beta asymmetry: This group comprises stocks with low gamma values but high beta values. These stocks have a lower sensitivity to negative shocks and asymmetry in volatility but a higher sensitivity to market movements. They may experience higher levels of volatility compared to the overall market, reflecting a potential for higher returns but also higher risk.

3) High Gamma, Low Beta asymmetry: This group includes stocks with high gamma values (indicating higher sensitivity to negative shocks and asymmetry in volatility) but low beta values (indicating lower sensitivity to market movements).

These stocks may be more prone to downside risk and exhibit greater volatility during market downturns. They are considered defensive stocks and could potentially provide downside protection during turbulent market conditions.

4) High Gamma, High Beta asymmetry: This group consists of stocks with both high gamma values and high beta values. These stocks are expected to have higher sensitivity to both negative shocks and market movements. They may exhibit higher volatility and potential for both higher returns and downside risk.

Figure 4 Portfolio groupings based on selection criteria used for evaluation.



Evaluating the performance of an investment portfolio is crucial for investors seeking to assess the effectiveness of their investment strategies and make informed decisions.

While there are various metrics available to measure portfolio performance, three key indicators that provide valuable insights are yearly return, Standard deviation, the Sharpe ratio, Paired Two-Sample t-Test for Means and RoMaD (Return on Maximum Drawdown).

Paired Two-Sample t-Test for Means, The t-Test is a parametric statistical hypothesis test for determining if there is a significant difference between the means of two related groups. The paired two-sample t-Test, in particular, is employed to compare the means of two related samples. In the context of this research, we utilize the paired two-sample t-Test to compare the mean returns of different portfolios to ascertain whether any significant difference exists between them.

Given two related sets of data, the paired two-sample t-Test investigates whether the means of these sets are statistically different. This test is most suitable when:

1. The two samples are independent.

2. The two samples are random samples from their respective populations.

3. The samples come from populations that follow a normal distribution, or the sample size is sufficiently large to rely on the Central Limit Theorem.

For mathematical representation, Let $X_1,\ X_2, ..., X_n$ and $Y_1, Y_2, ..., Y_n$ be the observed values from two samples. The differences between paired observations are $D_i = X_i - Y_i$. The paired two-sample t-Test for means can be represented as:

$$t = \frac{\bar{D}}{S_D/\sqrt{n}} \qquad (11)$$

Where:

$\bar{D}$ is the mean of the differences.

S_D is the standard deviation of the differences.

n is the number of observations.

In our study, the paired two-sample t-Test is utilized to determine whether the mean returns of two distinct portfolios are statistically different. By comparing the returns, we aim to uncover insights regarding the performance of the portfolios over specified periods.

The paired two-sample t-Test offers a rigorous statistical method to compare mean returns of portfolios, providing investors and researchers with a foundation to make informed decisions based on the relative performance of different investment strategies. By employing this test in our methodology, we ensure a robust analytical approach to understanding the dynamics of portfolio returns in the Thai stock market..

The Sharpe ratio, another widely used performance metric, assesses the risk-adjusted return of a portfolio. By considering both the portfolio's returns and its volatility or risk, the Sharpe ratio provides a measure of the excess return earned per unit of risk taken. A higher Sharpe ratio indicates a better risk-adjusted performance, as the portfolio is generating higher returns relative to its level of volatility.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{12}$$

where:

R_p = return of portfolio

R_f = risk-free rate

σ_p = standard deviation of the portfolio’s excess return

RoMaD, or Return on Maximum Drawdown, focuses on the portfolio's ability to recover from losses. It considers the largest peak-to-trough decline in the portfolio's value, known as the maximum drawdown, and evaluates the return generated relative to this decline. A higher RoMaD suggests that the portfolio has achieved better returns relative to the magnitude of its worst loss, reflecting a more favorable risk-return profile.

$$Maximum\ Drawdown\ (MDD) = \frac{Trough\ Value - Peak\ Value}{Peak\ Value} \tag{13}$$

$$RoMaD = \frac{Portfolio\ Return}{Maximum\ Drawdown} \tag{14}$$

CHAPTER 5 : EMPIRICAL RESULT

5.1 Data Analysis

To assess the asymmetric shocks on volatility within Thailand's financial market, we scrutinized an extensive dataset of stocks from the SET100 and sSET indexes. These indexes offer a holistic representation of firms traded on the Stock Exchange of Thailand (SET). The data, sourced from the Bloomberg database, spans from January 2018 to December 2022, encapsulating a notable 5-year period. This duration facilitates an in-depth analysis of the historical performance of the SET100 and sSET indexes, as well as the behavioral dynamics of the constituent companies. Additionally, the analysis segmented this timeframe into periods of market downturn (from 2018 to the first quarter of 2020) and market upturn (from the second quarter of 2020 to 2022).

5.2 Portfolio Construction and Categorization

In our empirical analysis, we organized stocks from the dataset into portfolios based on their individual gamma and combined coefficients of beta (specifically, $\boldsymbol{\beta_2}$ + $\boldsymbol{\beta_3}$). To streamline our discussion, we will refer to the sum of $\boldsymbol{\beta_2}$ and $\boldsymbol{\beta_3}$ simply as "Beta" in the sections that follow.

We then sorted these stocks into four distinct portfolios, each containing 20 stocks, derived from our gamma and beta categorization. The portfolios are:

1. HH (High Gamma, High Beta)

2. HL (High Gamma, Low Beta)

3. LH (Low Gamma, High Beta)

4. LL (Low Gamma, Low Beta)

A brief description of each portfolio classification

HH (High Gamma, High Beta): Stocks in this category display a pronounced sensitivity to negative market shocks, represented by their high gamma values, paired with a significant reactivity to broader market trends, as captured by their high beta values.

HL (High Gamma, Low Beta): These stocks possess high gamma values, indicative of their heightened reaction to adverse market events. However, their low beta values point towards a muted response to general market movements.

LH (Low Gamma, High Beta): Constituent stocks of this category are characterized by a subdued sensitivity to negative shocks (as denoted by their low gamma) but exhibit pronounced responsiveness to general market dynamics due to their high beta values.

LL (Low Gamma, Low Beta): This category encompasses stocks that are less responsive to both negative market events (low gamma) and general market trends (low beta), making them the most stable cohort within our classifications.

Our methodological approach to portfolio construction offers insights into the behavior of stocks under different market scenarios, catering to diverse risk profiles and investment objectives.

Given our portfolio classifications based on gamma and beta, it's imperative to revisit the underlying mechanics of gamma, particularly in the GJR-GARCH model, to elucidate the nuanced behavior of these stock categories.

As previously detailed:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1}}$$

The term $\boldsymbol{\gamma \varepsilon_{t-1}^2 d_{t-1}}$captures the asymmetry in the volatility response to negative shocks.

Explanation of Gamma's value

1. High Positive Value of γ ($\gamma > 0$)

- It indicates that negative shocks (i.e., negative returns) increase volatility more than positive shocks of equal magnitude. A higher positive γ means this effect is stronger. If the stock market experiences a negative return, the conditional volatility will increase by a magnitude that is proportional to the value of γ.

2. Negative Value of γ ($\gamma < 0$):

- This is less common in financial data, but if present, it would suggest an inverse asymmetry, where positive shocks would increase volatility more than negative shocks of the same magnitude. Given the context, this interpretation might be counterintuitive for many financial time series, as typically negative shocks are associated with higher subsequent volatility.

In the context of the equation, γ quantifies the extra volatility that stems from a negative shock, relative to a positive shock of the same magnitude. The overall impact of a negative shock on volatility is driven by $\boldsymbol{\alpha_1\, \varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2}$ when $\boldsymbol{\varepsilon_{t-1}} < 0$. If γ is high, the contribution of the asymmetric term becomes more pronounced, further accentuating the increase in volatility following a negative shock.

To provide a comprehensive understanding of stock behavior in our portfolios, we need to incorporate not only the gamma parameter from the GJR-GARCH model but also the beta coefficients from the following equation:

$$\boldsymbol{r_{it} = \alpha_i + \beta_{1i} r_{mt} + \beta_{2i} D_t r_{mt} + \beta_{3i} N_t r_{mt} + \varepsilon_{it}}$$

For $\boldsymbol{\beta_2 + \beta_3}$, These coefficients account for the specific market conditions, represented by $\boldsymbol{D_t}$ and $\boldsymbol{N_t}$, respectively. When these dummy variables are active (take the value of 1), the respective beta coefficients measure the stock's sensitivity to these conditions.

$\boldsymbol{\beta_2}$ measures stock's additional response to market returns during downturns. If $\boldsymbol{\beta_2}$ is positive, it implies that the stock's returns tend to move in the same direction as the market during downturns, and vice versa.

$\boldsymbol{\beta_3}$ captures the sensitivity of stock's returns to the market during upturns. A positive $\boldsymbol{\beta_3}$ suggests that during positive market conditions, the stock's returns align with the market's direction, while a negative value indicates the opposite.

5.3 Asymmetric Shock on Volatility

The analysis of asymmetric shocks on volatility revolves around the measurement of the gamma metric across the four portfolios. Gamma signifies the sensitivity of stock returns to negative shocks, capturing their potential asymmetric reaction to adverse market movements.

From **Table 1:** provides a brief summary of summary statistics for Gamma during the Market Downturn (2018-2020Q1)

HG,HB Portfolio: This high gamma, high beta portfolio exhibits an average gamma value of 0.1249, which indicates a relatively positive sensitivity to negative market events during the downturn. The gamma values span between 0.0094 and 0.4950, with a standard deviation of 7.65%.

HG,LB Portfolio: Stocks in this high gamma, low beta portfolio possess an average gamma of 0.1173, demonstrating a moderate positive sensitivity to adverse market movements. The gamma fluctuates between -0.0986 and 0.4467, with a variability of 7.83%.

LG,HB Portfolio: With an average gamma of -0.1201, the low gamma, high beta portfolio shows a negative sensitivity to negative shocks, implying these stocks typically decrease in value less than the market during negative events. The range of gamma values for this portfolio is notably wide, from -0.5737 to -0.0020, suggesting a considerable variability among the constituent stocks.

LG,LB Portfolio: This portfolio, consisting of low gamma and low beta stocks, displays the most negative average gamma at -0.1328. This indicates that these stocks are the least responsive to negative shocks, with gamma values stretching from an extreme -1.0000 to a slight positive of 0.0513. The standard deviation is the highest among the portfolios at 11.84%, indicating significant variability.

The observed gamma values during the market downturn suggest varying degrees of stock sensitivities across portfolios. While high gamma portfolios (HG,HB and HG,LB) demonstrated positive sensitivities to negative market events, the low gamma portfolios (LG,HB and LG,LB) generally showcased negative sensitivities, particularly underlining the defensive nature of the LG,LB stocks during market downturns.

Table 1 summary statistics for Gamma during the Market Downturn (2018-2020Q1)

Measure	Mean	Standard Deviation	Max	Min	No.of Stocks
HG,HB	0.1249	7.65%	0.4950	0.0094	180
HG,LB	0.1173	7.83%	0.4467	-0.0986	180
LG,HB	-0.1201	10.18%	-0.0020	-0.5737	180
LG,LB	-0.1328	11.84%	0.0513	-1.0000	180

From **Table 2 :** provides a brief summary of summary statistics for Gamma during the Market Upturn (2020Q2-2022)

HG,HB Portfolio: During the market upturn, this high gamma, high beta portfolio has an average gamma value of 0.1118. This suggests a slightly positive sensitivity to negative market shocks, even during favorable market conditions. The gamma values range between -0.0406 and 0.6771, with a standard deviation of 9.05%

HG,LB Portfolio: Stocks within this high gamma, low beta portfolio exhibit an average gamma of 0.1130, indicating a somewhat positive sensitivity to adverse market events during the upturn. The gamma values fluctuate between -0.0388 and 0.5260, with a standard deviation of 9.12%.

LG,HB Portfolio: This portfolio displays an average gamma of -0.1498, suggesting a negative sensitivity to negative shocks during the upturn period. The gamma values for this portfolio have a broad span, ranging from -0.7632 to 0.0397, implying significant variability among its stocks, with a standard deviation of 12.81%.

LG,LB Portfolio: With the most negative average gamma value of -0.1672, this portfolio, consisting of low gamma and low beta stocks, indicates a very limited responsiveness to negative shocks during favorable market conditions. Gamma values stretch from an extreme -1.0000 to a slight positive of 0.0363, with the highest standard deviation of 15.60% among the portfolios.

During the market upturn from 2020Q2 to 2022, the gamma values reflect differing sensitivities across portfolios. The high gamma portfolios (HG,HB and HG,LB) maintain slight positive sensitivities to negative market events, even in favorable conditions. In contrast, the low gamma portfolios (LG,HB and LG,LB) display more pronounced negative sensitivities, with the LG,LB stocks being the least responsive to negative events, reinforcing their stability even during market upturns.

Table 2 summary statistics for Gamma during the Market Upturn (2020Q2-2022)

Measure	Mean	Standard Deviation	Max	Min	No.of Stocks
HG,HB	0.1118	9.05%	0.6771	-0.0406	220
HG,LB	0.1130	9.12%	0.5260	-0.0388	220
LG,HB	-0.1498	12.81%	0.0397	-0.7632	220
LG,LB	-0.1672	15.60%	0.0363	-1.0000	220

5.3.1 Identification of Asymmetric Shock on Volatility

Our empirical analysis yields compelling insights into the asymmetric behavior of stocks when confronted with market shocks, particularly with regard to their gamma values across the portfolios. Through a thorough examination of gamma values across various portfolios during diverse market phases, we are able to discern and substantiate the presence of distinct patterns of asymmetric volatility reactions. These patterns shed light on how different portfolios, characterized by their gamma profiles, respond to both negative and positive market events, ultimately contributing to our understanding of the intricacies of risk and return in financial markets.

1. High Gamma Portfolios (HG,HB and HG,LB)

These portfolios consistently displayed positive gamma values in both market downturn (2018-2020Q1) and upturn (2020Q2-2022). Specifically, the HG,HB portfolio exhibited gamma values of 0.1249 during the downturn and 0.1118 during the upturn. Similarly, the HG,LB portfolio had gamma values of 0.1173 and 0.1130 for the respective periods.

- The consistent positive gamma values indicate that stocks within these portfolios had an amplified sensitivity to negative market shocks, even during favorable market conditions. This heightened reactivity signifies an asymmetric response, where the volatility of these stocks increases more than proportionally in response to negative events.

2. Low Gamma Portfolios (LG,HB and LG,LB)

During both market phases, these portfolios consistently showcased negative gamma values. For the LG,HB portfolio, the gamma was -0.1201 during the downturn and -0.1498 during the upturn. For the LG,LB portfolio, the values were -0.1328 and -0.1672 respectively.

- The negative gamma values suggest a muted response to negative shocks. This means that as the market faced adverse events, the stocks in these portfolios exhibited lesser volatility, indicating a form of resilience or decreased sensitivity to negative events.

The observed gamma values across the portfolios provide strong evidence of asymmetric shocks on volatility. Stocks in the high gamma portfolios consistently show heightened sensitivity to negative market events, making them more volatile and risk-prone in the face of adverse shocks. Conversely, stocks in the low gamma portfolios display a form of protective resilience, with their volatility being less influenced by negative market events.

This asymmetry in volatility reactions underscores the significance of understanding the inherent risk characteristics of portfolios. It also emphasizes the potential benefits of diversification, where investors can balance their holdings between high and low gamma stocks to navigate the complexities of market shocks.

5.4 Asymmetry of Beta

Analysis of Beta Coefficients and Asymmetry in Market Sensitivity

The analysis of beta coefficients across diverse portfolios provides crucial insights into how stocks react to overall market movements. Beta, a fundamental metric for gauging systematic risk, illuminates the relationship between individual stocks or portfolios and the broader market. It is essential to note that a positive beta signifies a tendency for stocks to move in harmony with the market, while a negative beta indicates an inverse relationship.

During the market downturn phase from 2018 to the first quarter of 2020, from **Table 3**, our analysis reveals the following insights into the asymmetry of beta coefficients across various portfolios:

HG,HB Portfolio (High Gamma, High Beta): This portfolio displays a mean beta of 0.2196, indicating a positive correlation with the market during the downturn. However, the wide range between the maximum and minimum beta values suggests significant variability among individual stock betas within this portfolio. This variance underscores the asymmetric nature of market sensitivity exhibited by these stocks during adverse market conditions.

HG,LB Portfolio (High Gamma, Low Beta): With a mean beta of -0.5460, this portfolio tends to move inversely to the broader market during downturns. The presence of a large negative minimum beta value highlights that certain stocks within this portfolio exhibit strong inverse reactions to market movements, contributing to the overall negative mean beta. This stark asymmetry in market sensitivity is evident within this portfolio.

LG,HB Portfolio (Low Gamma, High Beta): Similar to the HG,HB portfolio, this portfolio displays a positive correlation with the market during the downturn, with a mean beta of 0.2394. However, the slightly higher mean beta indicates that stocks within this category are somewhat more sensitive to overall market movements during downturns. This variation in sensitivity among the constituent stocks underscores the asymmetry in their market reactions.

LG,LB Portfolio (Low Gamma, Low Beta): This portfolio exhibits a negative mean beta of -0.5578, signifying an inverse relationship with the market during the downturn. The substantial spread between the maximum and minimum beta values highlights the pronounced inverse relationship displayed by some stocks within this portfolio, emphasizing the asymmetry in their market sensitivity.

Table 3 summary statistics for Beta during the Market Downturn (2018-2020Q1)

Measure	Mean	Standard Deviation	Max	Min	No.of Stocks
HG,HB	0.2196	26.54%	1.2980	-0.1597	180
HG,LB	-0.5460	40.15%	1.2187	-2.2293	180
LG,HB	0.2394	26.50%	1.3872	-0.0696	180
LG,LB	-0.5578	35.16%	1.3630	-2.8152	180

During the market upturn phase from the second quarter of 2020 to 2022, from **Table 4**, our analysis reveals the following insights:

HG,HB Portfolio (High Gamma, High Beta): Stocks within this portfolio continue to display a positive correlation with the market, with a mean beta of 0.2200. The diverse range of sensitivities among the constituent stocks, as indicated by the spread between the maximum and minimum beta values, underscores the asymmetric nature of their market sensitivity, even during favorable market conditions.

HG,LB Portfolio (High Gamma, Low Beta): This portfolio maintains its inverse relationship with the broader market during the upturn, with a mean beta of -0.4514. The presence of a pronounced negative minimum beta value indicates that certain stocks within this portfolio exhibit strong inverse reactions to market changes, contributing to the overall negative mean beta. This asymmetry persists in their market sensitivity.

LG,HB Portfolio (Low Gamma, High Beta): Stocks within this portfolio continue to exhibit a positive average beta of 0.1525, suggesting a tendency to move with the market during the upturn. However, the range of sensitivities among the stocks, with some even displaying a mild negative correlation, highlights the asymmetry in their market reactions.

LG,LB Portfolio (Low Gamma, Low Beta): This portfolio maintains its inverse relationship with the market during the upturn, with a negative mean beta of -0.5492. The substantial spread between the maximum and minimum beta values underscores the pronounced inverse relationship displayed by some stocks within this portfolio, reaffirming the asymmetry in their market sensitivity.

Table 4 summary statistics for Beta during the Market Upturn (2020Q2-2022)

Measure	Mean	Standard Deviation	Max	Min	No.of Stocks
HG,HB	0.2200	22.98%	1.1644	-0.2936	220
HG,LB	-0.4514	31.04%	-0.0693	-1.4847	220
LG,HB	0.1525	30.68%	1.7268	-0.4572	220
LG,LB	-0.5492	34.37%	-0.0899	-2.2108	220

The practice of rebalancing portfolios every quarter can lead to the observed crossing over of gamma and beta values within different portfolio categories across quarters. This phenomenon may stem from the inherent variability of the investment market or the broader economic conditions prevailing at the time. The summary statistics provided for both the downturn and upturn periods demonstrate that the gamma and beta of individual stocks do not remain constant but are affected by both systemic factors and stock-specific events.

During the downturn, the beta values exhibited significant volatility, reflecting the sensitivity of stocks to the tumultuous market. Conversely, in the upturn, although the mean beta values improved, indicating better performance relative to the market, the gamma values displayed varied changes, highlighting the difference in stock-specific risks.

In essence, the rebalancing acts as a mechanism to adjust to these fluctuations. Portfolios that were once aligned with previous market conditions are re-optimized to cater to new realities, which might involve taking on stocks with different gammas (indicating a change in the risk of an asset) and betas (indicating how much the stock is expected to move in relation to market movements). As market conditions evolve, the compositions of these portfolios shift, often resulting in the crossover of gamma and beta values, as stocks previously labeled as high gamma or high beta may not retain those characteristics in the new market conditions.

5.4.1 Identification of Asymmetry of Beta

In our comprehensive analysis, we have consistently observed an intriguing pattern of asymmetry in beta coefficients, regardless of whether the market is experiencing a downturn or an upturn. This asymmetry becomes apparent when we closely examine how individual stocks within each portfolio react to broader market movements. Some stocks within these portfolios demonstrate notably stronger correlations with the market, either in a positive or negative direction, and this variability contributes to the observed asymmetry in the overall portfolio beta values.

When discussing the asymmetry in beta coefficients, we are essentially highlighting the fact that not all stocks within a given portfolio behave in the same way in response to market fluctuations. Some stocks are more closely aligned with the market's movements, meaning they tend to move in the same direction as the market, whether it's upward or downward. Conversely, other stocks within the same portfolio exhibit a divergent behavior, moving in the opposite direction of the market. This divergence creates an inherent asymmetry within the portfolio's beta values.

5.5 Analysis of Stock Frequencies in Different Portfolios over Two Time Periods

To better understand the consistency of stock inclusion within specific portfolios during two distinct time frames, we have examined the frequencies of stocks that appeared in these portfolios. This analysis sheds light on the stability and persistence of stock selections over the periods 2018-2020Q1 and 2020Q2-2022. The following **Table 5**, presents the results of this investigation, offering insights into the dynamic nature of portfolio compositions.

Table 5 Summary stock frequencies in different portfolios over two time periods

Portfolio	2018 - 2020Q1		2020Q2 - 2022	
	Stocks	Frequency (out of 9)	Stocks	Frequency (out of 11)
HG,HB	DELTA TB Equity	6	PTT TB Equity	9
	BBL TB Equity	6		
HG,LB	LPH TB Equity	4	NNCL TB Equity	5
	MCS TB Equity	4	PF TB Equity	5
	SUSCO TB Equity	4	TKN TB Equity	5
	SUPER TB Equity	4	JAS TB Equity	5
	THAI TB Equity	4	MCS TB Equity	5
	SYNEX TB Equity	4		
	EPG TB Equity	4		
	MC TB Equity	4		
	AAV TB Equity	4		
LG,HB	CKP TB Equity	4	GFPT TB Equity	6
	SAT TB Equity	4	KAMART TB Equity	6
	CENTEL TB Equity	4		
	PTT TB Equity	4		
	IVL TB Equity	4		
	CPF TB Equity	4		
	RATCH TB Equity	4		
LG,LB	ROJNA TB Equity	6	MC TB Equity	7

5.6 Analysis of Portfolio Selections: Scatter Plot Trends Based on Gamma and Beta Values in the First Quarter of 2018.

From **Figure 5 to 8** represent the scatter plots of each portfolio, including all stocks, for the first quarter of 2018.0

Figure 5 Portfolio with HG,HB (2018Q1)

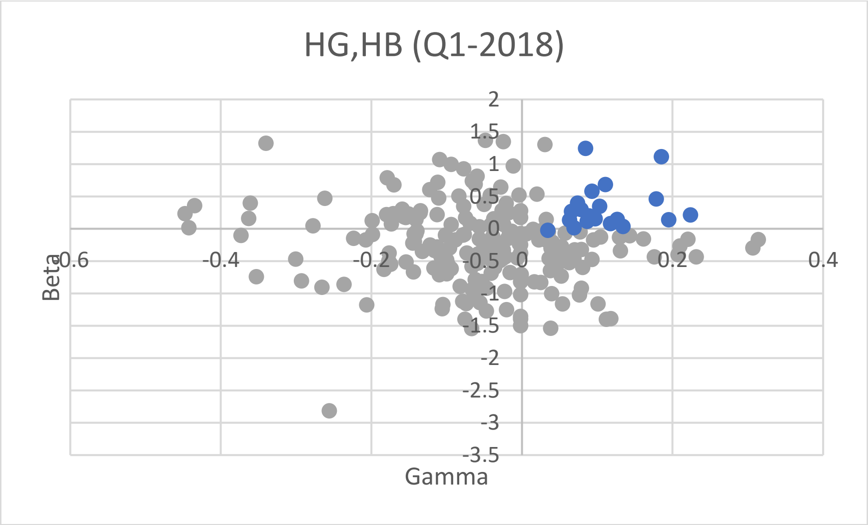


Figure 6 Portfolio with HG,LB (2018Q1)

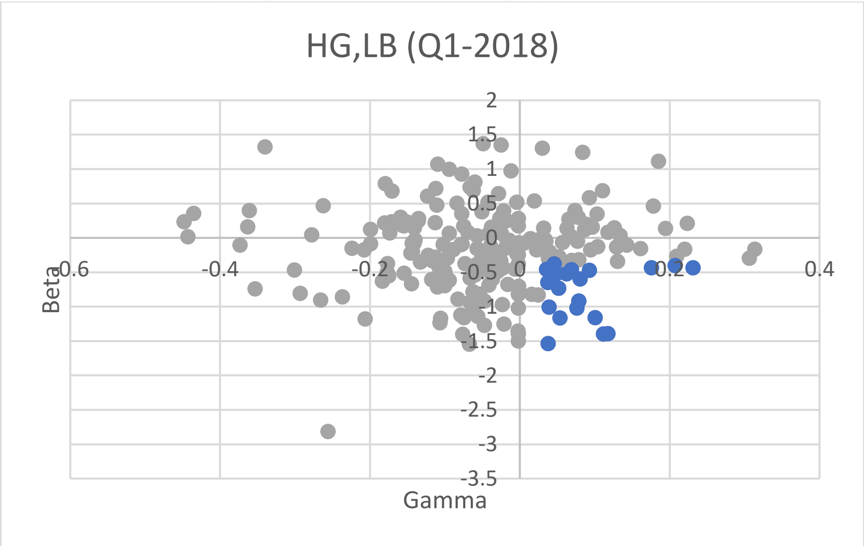


Figure 7 Portfolio with LG,HB (2018Q1)

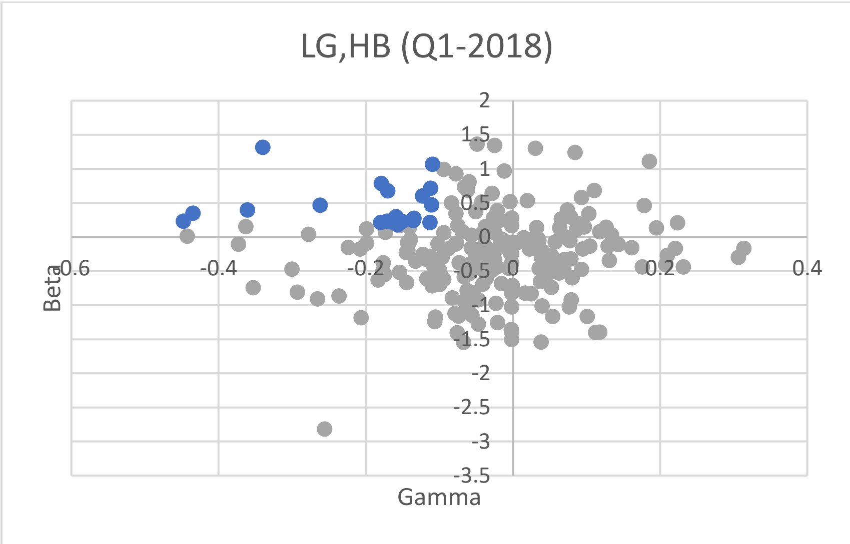
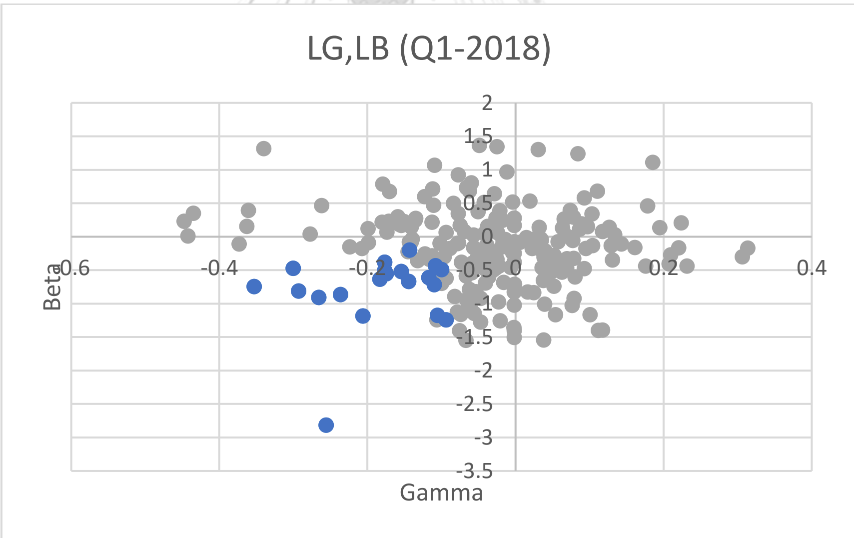


Figure 8 Portfolio with LG,LB (2018Q1)



5.7 Analysis of Portfolio Selections: Scatter Plot Trends Based on Low Gamma and High Beta Values During Market Downturn and Upturn Periods

From **Figure 9 and 10** represent the scatter plots of portfolio with Low Gamma and High Beta, During Market Downturn and Upturn Periods.

Figure 9 Portfolio with LG,HB (Market Downturn)

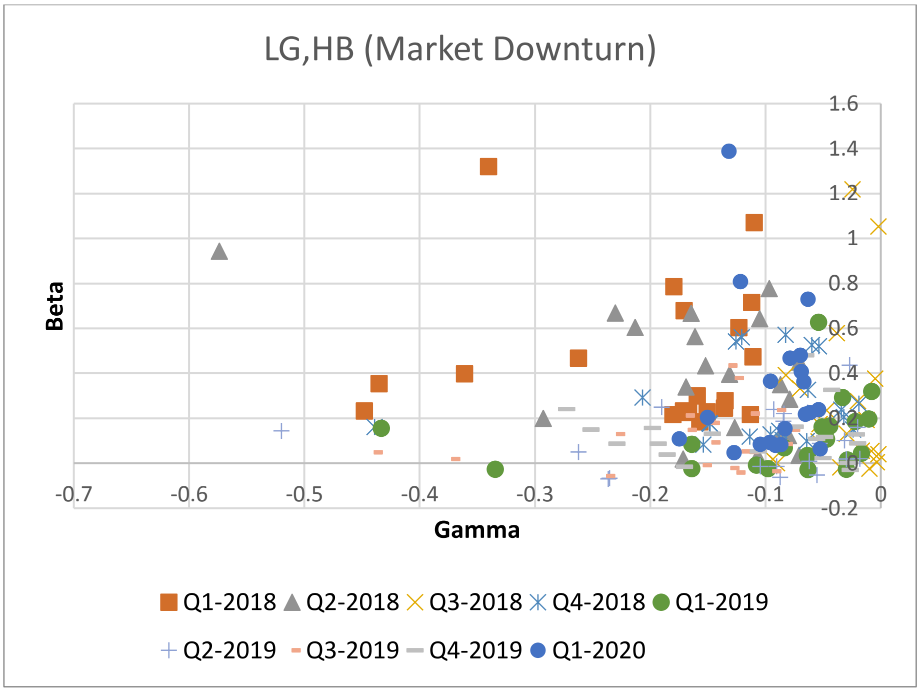
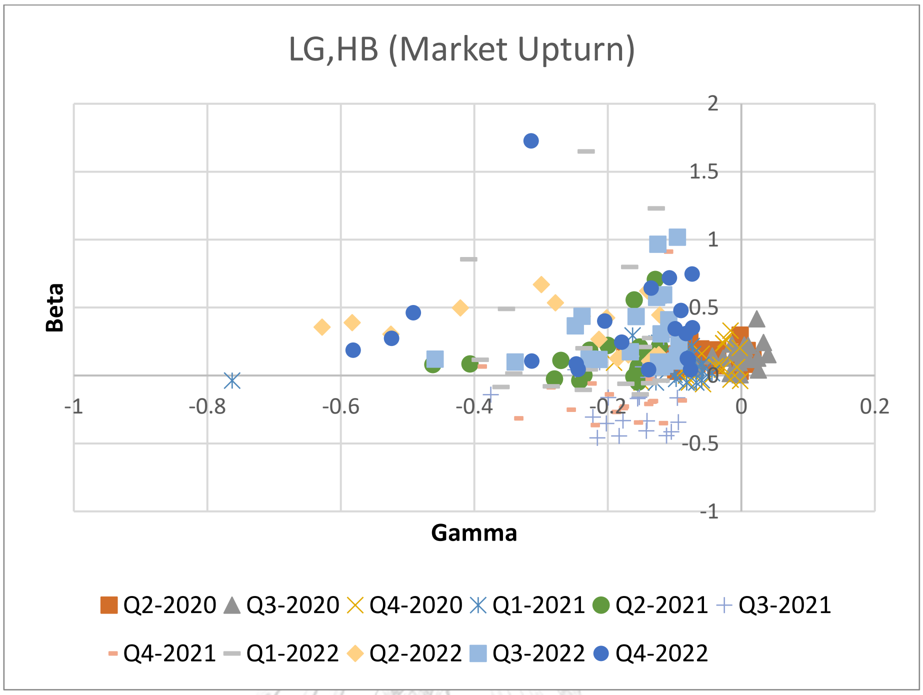


Figure 10 Portfolio with LG,HB (Market Upturn)



5.8 Portfolio Performance Analysis

From **Table 6**, during the challenging market conditions from 2018 to 2020Q1, all portfolios experienced negative returns, reflecting the broader market downturn. In this period:

HG,HB portfolio registered a significant negative return of -39.34%, accompanied by a Sharpe ratio of –1.89, indicating a suboptimal risk-adjusted performance.

HG,LB followed a similar trend with a return of -41.63% and a Sharpe ratio of -1.97.

LG,HB portfolio exhibited relatively better performance, recording a decline of -29.75% and a Sharpe ratio of -1.54.

LG,LB faced the most substantial decline, with a return of -42.50% and a Sharpe ratio of -2.06, implying even higher risk relative to its return.

In comparison, the SET TRI portfolio had the least decline in returns, registering at -17.56%.

From **Table 6**, during the market recovery from 2020Q2 to 2022, the portfolios displayed varying degrees of recuperation:

HG,HB portfolio exhibited a return of 12.45%. Despite the positive return, the Sharpe ratio of 0.59.

HG,LB displayed slightly better performance with a return of 13.36% and a Sharpe ratio of 0.68.

LG,HB emerged as the best performer during this period, achieving a substantial return of 21.82% and Sharpe ratio of 1.13, indicating improved risk-adjusted returns.

Conversely, LG,LB showed a marginal return of 0.26%, with a Sharpe ratio of -0.05, signifying that it still carried significant risk relative to its return and suggesting that risk-adjusted returns were not optimal.

The SET TRI portfolio demonstrated a robust recovery, achieving a return of 18.02%.

In conclusion, these portfolio performance findings illustrate the diverse impact of market conditions on different portfolio compositions. While all portfolios experienced downturns during challenging market phases, some displayed more resilience and effective recovery strategies during favorable periods. These insights provide valuable information for portfolio management and risk assessment in navigating dynamic market environments.

Table 6 portfolios performance over two time periods

Portfolio	2018 - 2020Q1			2020Q2 - 2022		
	Return	Sharpe Ratio	Standard Deviation	Return	Sharpe Ratio	Standard Deviation
HG,HB	-39.34%	-1.89	21.62%	12.45%	0.59	18.91%
HG,LB	-41.63%	-1.97	21.90%	13.36%	0.68	17.67%
LG,HB	-29.75%	-1.54	20.27%	21.82%	1.13	18.12%
LG,LB	-42.50%	-2.06	21.38%	0.26%	-0.05	22.09%
SET TRI	-17.56%		18.87%	18.02%		14.88%

In our analysis, a series of figures visually represent the portfolio performances over distinct periods, capturing the essence of their returns in various market conditions.

From **Figure 11**, presents a comprehensive overview of the cumulative returns of each portfolio from 2018 through 2022. This broad time frame encompasses both upturn and downturn periods, providing a holistic view of the portfolio performances over consecutive years. By analyzing this figure, investors can trace the trajectory of returns, noting the inflection points and the relative resilience or volatility of each portfolio over the entire period.

From **Figure 12**, zooms in on a more specific period, the market downturn that spanned from 2018 to the first quarter of 2020. This figure elucidates how each portfolio navigated the challenges of a contracting market. By examining the curves and trends during this period, one can discern which portfolios were more susceptible to market pressures and which demonstrated a degree of immunity against the larger downward pull.

Contrastingly, From **Figure 13**, shifts the lens to a period of market resurgence. Documenting the market upturn from the second quarter of 2020 to 2022, this figure portrays the rally and recovery patterns of the portfolios. The nuances of this figure shed light on which portfolios capitalized most effectively on the rebounding market conditions and which lagged in harnessing the upturn momentum.

Collectively, these figures provide a visual narrative of portfolio behaviors in distinct market phases, helping stakeholders to evaluate and strategize for future investment scenarios.

Figure 11 Cumulative return performance of portfolios & SETTRI (2018-2022)

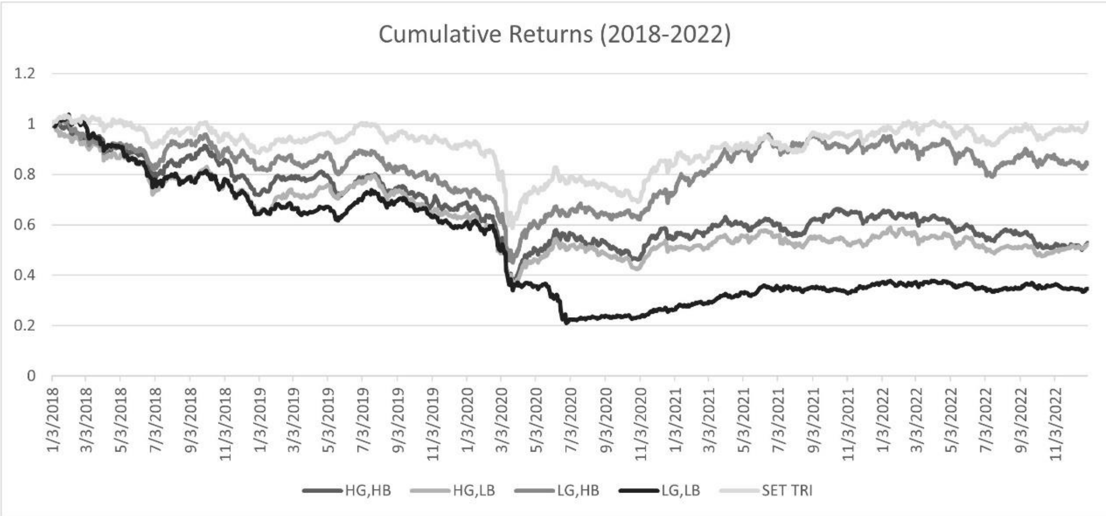


Figure 12 Cumulative return performance of portfolios & SETTRI (2018-2020Q1)

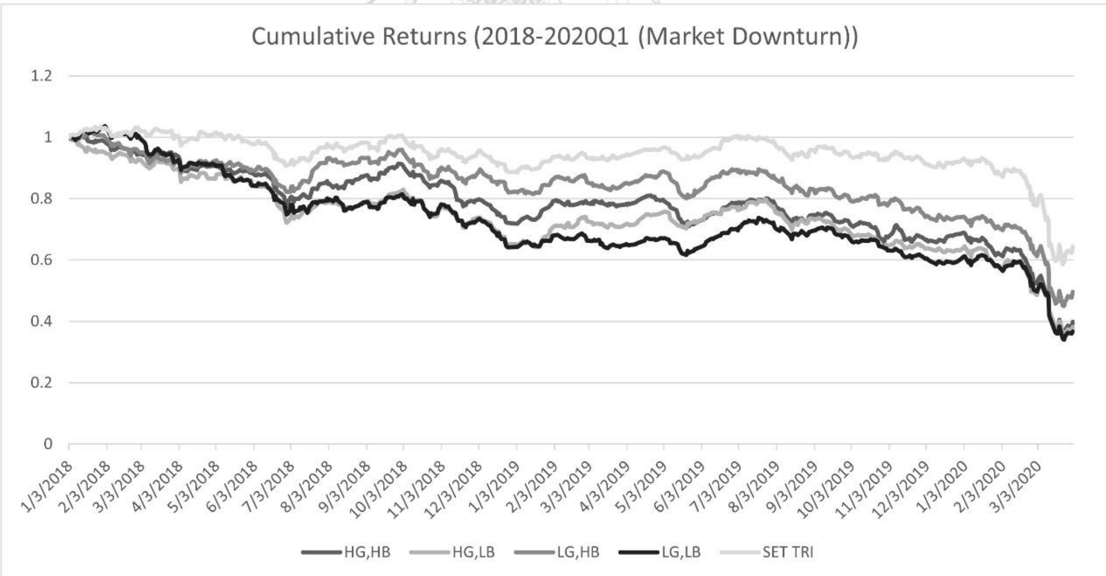
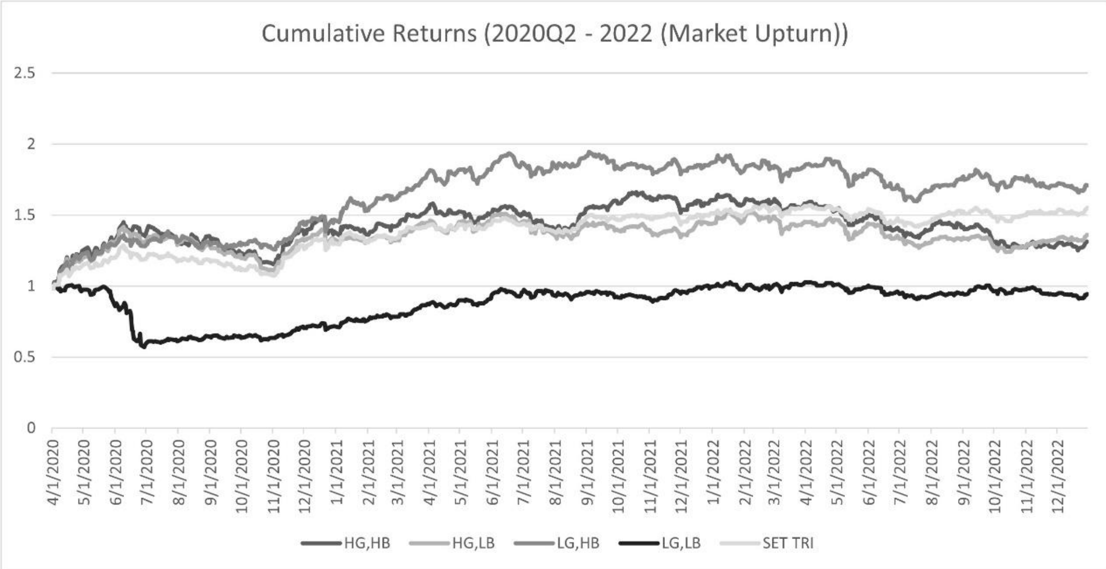


Figure 13 Cumulative return performance of portfolios & SETTRI (2020Q2-2022)



RoMaD

Examining the data between 2018 and 2022, the provided table sheds light on two crucial metrics for the portfolios: Maximum Drawdown and Return on Maximum Drawdown (RoMaD). These metrics provide insights into the risk profiles of portfolios and their risk-adjusted performance.

Interpreting the Maximum Drawdown (Max Drawdown) and Return on Maximum Drawdown (RoMaD) for the portfolios from **Table 7**:

HG,HB: Experienced a maximum drawdown of 64.08% and has a negative RoMaD of -0.1736. This suggests that for the amount of downside risk taken, the return was negative, implying a less efficient performance.

HG,LB: Had a similar maximum drawdown to HG,HB at 64.68% but with a slightly lower RoMaD of -0.1804, indicating that it also did not utilize risk efficiently, possibly performing slightly worse than the HG,HB portfolio in terms of risk-adjusted return.

LG,HB: This portfolio had a lower maximum drawdown at 55.83% compared to the high gamma portfolios, and a much smaller (less negative) RoMaD of -0.0296, suggesting that it managed risk more efficiently than the high gamma portfolios.

LG,LB: Experienced the highest maximum drawdown at 79.80% and the lowest (most negative) RoMaD of -0.2407, indicating that this portfolio had the least efficient performance of all the portfolios listed, with the highest relative loss per unit of risk taken.

SET TRI: This appears to be a benchmark index (likely the Stock Exchange of Thailand Total Return Index), and it shows a maximum drawdown significantly lower than that of any of the portfolios at 43.22%. Furthermore, it is the only one with a positive RoMaD at 0.0423, indicating that, over this time period, the benchmark index provided a positive return per unit of risk, outperforming all the listed portfolios in terms of risk-adjusted returns.

According to these metrics, all portfolios except for the SET TRI had negative returns when considering the risk taken (as measured by drawdown), with the LG,LB portfolio showing the worst risk-adjusted performance and the LG,HB portfolio the best among the negative ones. The SET TRI outperformed all specific portfolios in this regard.

Table 7 Maximum Drawdown and RoMaD of each portfolio over full periods

Portfolio	2018-2022	
	Maximun Drawdown	RoMaD
HG,HB	64.08%	-0.1736
HG,LB	64.68%	-0.1804
LG,HB	55.83%	-0.0296
LG,LB	79.80%	-0.2407
SET TRI	43.22%	0.0423

5.8.1 Analysis of Portfolio Mean Differences during Market Downturn (2018 – 2020Q1)

During our examination of portfolio performances in the market downturn period, we employed t-tests to determine if there were any statistically significant differences in the means between various portfolios From **Table 8, 9 and 10.**

Comparative Analysis: LG,HB and HG,HB

t-Statistic Value: 1.374586

Critical t-Value (One-tail): 1.647619

p-Value (Two-tail): 0.169818

The observed t-statistic for the comparison between LG,HB and HG,HB portfolios is 1.374586, which is notably lower than the critical one-tailed t-value of 1.647619. Moreover, the associated two-tailed p-value of 0.169818 surpasses the 10% significance threshold. Consequently, this analysis does not provide sufficient evidence to reject the null hypothesis. This suggests that during the market downturn period, the LG,HB and HG,HB portfolios did not exhibit statistically different mean performances.

Comparative Analysis: LG,HB and HG,LB

t-Statistic Value: 1.637334

Critical t-Value (One-tail): 1.647619

p-Value (Two-tail): 0.102131

When comparing LG,HB and HG,LB portfolios, the calculated t-statistic of 1.637334 is marginally below the one-tailed critical value of 1.647619. The associated two-tailed p-value is 0.102131, slightly exceeding the 10% significance mark. These results present a borderline case, but based on conventional standards, the data does not provide enough evidence to reject the null hypothesis. This infers that the performance means of LG,HB and HG,LB remained statistically indistinguishable during the period in question.

Comparative Analysis: LG,HB and LG,LB

t-Statistic Value: 1.790593

Critical t-Value (One-tail): 1.647619

p-Value (Two-tail): 0.073907

For the LG,HB and LG,LB portfolio pairing, the derived t-statistic is 1.790593, surpassing the one-tailed critical threshold of 1.647619. The two-tailed p-value stands at 0.073907, falling below the 10% significance boundary. Thus, with a confidence level of 90%, we can reject the null hypothesis, indicating a significant mean difference between the LG,HB and LG,LB portfolios during the market downturn.

Additionally, to further optimize decisions, considering long and short portfolios offers a strategic perspective. For instance, adopting a strategy that involves taking long positions in the LG,HB portfolio while simultaneously shorting the LG,LB portfolio can act as a hedging mechanism. This approach serves to capitalize on the expected performance of the LG,HB while hedging against potential downturns with the LG,LB, aiming to minimize risk and potentially maximize returns.

These findings underscore the significance of portfolio selection tailored to specific market conditions. Notably, while LG,HB and HG,HB, as well as LG,HB and HG,LB, portrayed analogous mean outcomes during market downturns, the pairing of LG,HB and LG,LB revealed statistically distinct results. This denotes that, during market downturns, opting between LG,HB and LG,LB portfolios can drastically influence portfolio results. Additionally, integrating long and short strategies like Long LG,HB and Short LG,LB can further enhance decision-making, promoting both risk mitigation and return optimization.

Table 8 t-Test: Paired Two Sample for Means of LG,HB and HG,HB (Downturn Period)

	LG,HB	*HG,HB*
Mean	-0.00118	-0.00156
Variance	0.000163	0.000185
Observations	553	553
Pearson Correlation	0.880042	
Hypothesized Mean Difference	0	
df	552	
t Stat	1.374586	
P(T<=t) one-tail	0.084909	
t Critical one-tail	1.647619	
P(T<=t) two-tail	0.169818	
t Critical two-tail	1.964271	

Table 9 t-Test: Paired Two Sample for Means of LG,HB and HG,LB (Downturn Period)

	LG,HB	*HG,LB*
Mean	-0.00118	-0.00165
Variance	0.000163	0.00019
Observations	553	553
Pearson Correlation	0.872808	
Hypothesized Mean Difference	0	
df	552	
t Stat	1.637334	
P(T<=t) one-tail	0.051065	
t Critical one-tail	1.647619	
P(T<=t) two-tail	0.102131	
t Critical two-tail	1.964271	

Table 10 t-Test: Paired Two Sample for Means of LG,HB and LG,LB (Downturn Period)

	LG,HB	*LG,LB*
Mean	-0.00118	-0.00169
Variance	0.000163	0.000181
Observations	553	553
Pearson Correlation	0.872936	
Hypothesized Mean Difference	0	
df	552	
t Stat	1.790593	
P(T<=t) one-tail	0.036953	
t Critical one-tail	1.647619	
P(T<=t) two-tail	0.073907	
t Critical two-tail	1.964271	

5.8.2 Analysis of Portfolio Mean Differences during Market Upturn (2020Q2-2022)

In this section, we focus on the market upturn period, examining the performances of different portfolio combinations. Utilizing t-tests, we probe for statistically significant differences in their means, From **Table 11, 12 and 13.**

Comparative Analysis: LG,HB and HG,HB

t-Statistic Value: 1.175882

Critical t-Value (One-tail): 1.647162

p-Value (Two-tail): 0.240065

In the comparison between the LG,HB and HG,HB portfolios, our calculated t-statistic of 1.175882 falls below the one-tailed critical value of 1.647162. The accompanying two-tailed p-value, 0.240065, exceeds the 10% significance threshold. Based on this evidence, we find no substantial evidence to reject the null hypothesis, indicating that during the market upturn, there is no statistically significant difference between the means of the LG,HB and HG,HB portfolios.

Comparative Analysis: LG,HB and HG,LB

t-Statistic Value: 1.148439

Critical t-Value (One-tail): 1.647162

p-Value (Two-tail): 0.251203

In this pairing, the t-statistic of 1.148439, derived from the LG,HB and HG,LB portfolios, is beneath the one-tailed critical t-value of 1.647162. The two-tailed p-value is 0.251203, which again is above the 10% level of significance. As such, we find no substantial evidence to reject the null hypothesis, suggesting that the performance means of the LG,HB and HG,LB portfolios were not statistically different during this upturn period.

Comparative Analysis: LG,HB and LG,LB

t-Statistic Value: 1.60008

Critical t-Value (One-tail): 1.647162

p-Value (Two-tail): 0.110059

For the comparison between the LG,HB and LG,LB portfolios, our calculated t-statistic is 1.60008. This figure approaches but does not surpass the one-tailed critical value of 1.647162. The associated two-tailed p-value stands at 0.110059, slightly above the 10% significance mark. Thus, this analysis does not offer enough statistical evidence to reject the null hypothesis. This implies that, during the market upturn period, the means of the LG,HB and LG,LB portfolios were not statistically different.

Conclusion based on the analyses, none of the three portfolio pairings revealed a statistically significant difference in their mean performances during the market upturn at the 10% significance level.

Table 11 t-Test: Paired Two Sample for Means of LG,HB and HG,HB (Upturn Period)

	LG,HB	*HG,HB*
Mean	0.000866	0.000494
Variance	0.00013	0.000142
Observations	662	662
Pearson Correlation	0.75742	
Hypothesized Mean Difference	0	
df	661	
t Stat	1.175882	
P(T<=t) one-tail	0.120033	
t Critical one-tail	1.647162	
P(T<=t) two-tail	0.240065	
t Critical two-tail	1.963559	

Table 12 t-Test: Paired Two Sample for Means of LG,HB and HG,LB (Upturn Period)

	LG,HB	*HG,LB*
Mean	0.000866	0.00053
Variance	0.00013	0.000124
Observations	662	662
Pearson Correlation	0.777636	
Hypothesized Mean Difference	0	
df	661	
t Stat	1.148439	
P(T<=t) one-tail	0.125601	
t Critical one-tail	1.647162	
P(T<=t) two-tail	0.251203	
t Critical two-tail	1.963559	

Table 13 t-Test: Paired Two Sample for Means of LG,HB and LG,LB (Upturn Period)

	LG,HB	*LG,LB*
Mean	0.000866	1.02E-05
Variance	0.00013	0.000194
Observations	662	662
Pearson Correlation	0.42385	
Hypothesized Mean Difference	0	
df	661	
t Stat	1.60008	
P(T<=t) one-tail	0.055029	
t Critical one-tail	1.647162	
P(T<=t) two-tail	0.110059	
t Critical two-tail	1.963559	

CHAPTER 6 : CONCLUSION

The asymmetric shock on volatility and the asymmetry of beta play pivotal roles in shaping the behavior of the Thai stock market, particularly during periods of market fluctuations. Our extensive analysis reveals that portfolios consisting of stocks with a lower sensitivity to negative shocks and a higher responsiveness to overall market movements consistently outperform other portfolios. These results hold true for both market downturns and upturns.

The significance of these findings lies in their implications for investors and portfolio managers. Portfolios that strike a balance between resilience during adverse market conditions and the ability to capture gains during market upswings prove to be the most effective in optimizing investment performance and risk management.

Furthermore, our statistically significant results underscore the efficacy of adopting a long-short strategy. This strategy involves holding both portfolios that are less sensitive to negative shocks and more sensitive to market movements (long positions) and portfolios that are less sensitive to both negative shocks and market movements (short positions). By doing so, investors can effectively hedge against market volatility and minimize risk while simultaneously enhancing their investment performance.

Our research not only highlights the importance of considering asymmetry in portfolio construction but also provides a concrete strategy – the long-short strategy – that can serve as a valuable tool for investors looking to navigate the complexities of the Thai stock market. These findings offer a robust foundation for future portfolio management techniques, emphasizing the significance of balancing asymmetric risk factors for improved investment outcomes.

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