The analysis of enhanced momentum strategies in the Stock Exchange of Thailand

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การวิเคราะห์กลยุทธ์โมเมนตัมต่อยอดในตลาดหลักทรัพย์แห่งประเทศไทย

นายชยกรณ์ กมลสวัสดิ์

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วิทยานิพนธ์ฉบับนี้มีวัตถุประสงค์เพื่อศึกษาประสิทธิภาพของกลยุทธ์โมเมนตัมในพอร์ตการลงทุน ซึ่งกลยุทธ์โมเมนตัมเป็นความผิดปกติที่รู้จักกันดีในสมมติฐานประสิทธิภาพของตลาด โดยพอร์ตการลงทุนถูกสร้างขึ้นจากการซื้อกลุ่มหลักทรัพย์ที่มีผลตอบแทนในอดีตสูง และขายกลุ่มหลักทรัพย์ที่มีผลตอบแทนในอดีตต่ำ โดยเฉพาะอย่างยิ่ง การศึกษานี้มุ่งเน้นไปที่การใช้ความผันผวนเพื่อเสริมกลยุทธ์โมเมนตัมในตลาดหลักทรัพย์แห่งประเทศไทยตั้งแต่เดือนมกราคม 2556 ถึงธันวาคม 2565 ในการศึกษากลยุทธ์โมเมนตัมต่อยอดจะแปลผันน้ำหนักของพอร์ตการลงทุนตามความผันผวน สามารถจำแนกหลักการแปรผันน้ำหนักออกได้เป็น 3 หลักการ ดังนี้ 1. หลักการความผันผวนคงที่ 2. หลักการกึ่งความผันผวนคงที่ และ 3. หลักการพลวัต การวิจัยมีเป้าหมายเพื่อบรรลุวัตถุประสงค์หลักสองประการ ประการแรก เพื่อวิเคราะห์ศักยภาพของกลยุทธ์โมเมนตัมต่อยอด โดยการเปรียบเทียบผลตอบแทนเฉลี่ย อัตราส่วนชาร์ป และจุดขาดทุนสูงสุด ในขณะเดียวกันก็คำนึงถึงต้นทุนการทำธุรกรรม ซึ่งในการศึกษานี้แทนด้วยต้นทุนไป-กลับ ประการที่สอง เพื่อตรวจสอบลักษณะเฉพาะที่ผันแปรตามเวลาของหลักการเหล่านี้ และการระบุช่วงเวลาย่อยโดยใชการพังทลายของโมเมนตัมเป็นเกณฑ์ ซึ่งสัมพันธ์กับผลตอบแทนเชิงลบที่สม่ำเสมอของกลยุทธิโมเมนตัมแบบดั้งเดิม ช่วงเวลาเหล่านี้มักเกิดขึ้นระหว่างสภาวะตื่นตระหนกหลังจากตลาดขาลงและเกิดขึ้นพร้อมกับการฟื้นตัวอย่างรวดเร็วของตลาด นอกจากนี้ยังมีการวิเคราะห์ความไม่สมมาตรในระหว่างตลาดกระทิงและตลาดหมี

การศึกษานี้ค้นพบว่า กลยุทธ์โมเมนตันต่อยอดแสดงประสิทธิภาพเหนือกว่าโมเมนตัมมาตรฐาน ทั้งจากมุมมองทางเศรษฐกิจและทางสถิติ พอร์ตการลุงทุนที่มีการจัดการด้านความผันผวนเหล่านี้ปรับน้ำหนักในการลงทุนและควบคุมจังหวะในการจัดการความผันผวนของพอร์ตการลงทุนได้อย่างมีประสิทธิภาพ ซึ่งนำไปสู่ผลตอบแทนและอัตราส่วนชาร์ปที่ดีขึ้น นอกจากนี้ การศึกษายังเน้นย้ำถึงการพังทลายของกลยุทธ์โมเมนตัมที่เกิดขึ้นในตลาดหลักทรัพย์แห่งประเทศไทยซึ่งเริ่มตั้งแต่ต้นปี 2563 แม้ท่ามกลางวิกฤตการณ์ของตลาด เช่น การแพร่ระบาดของโรคโควิด-19 บางกลยุทธ์โมเมนตัมต่อยอดสามารถแสดงประสิทธิภาพได้ดีกว่าพอร์ทการลุงทุนมาตรฐาน โดยเฉพาะอย่างยิ่งหลักการพลวัต ซึ่งกลยุทธ์นี้นำผลตอบแทนที่คาดหวังมาประยุกต์กับการปรับปริมาณการลงทุน หลักการพลวัตนี้ช่วยให้พอร์ตการลงทุนได้รับผลตอนแทนสูงในช่วงที่เกิดการพังทลายของกลยุทธ์โมเมนตัม นอกจากนี้ การศึกษายังระบุว่า โดยทั่วไปแล้วกลยุทธ์โมเมนตัมสามารถจัดการต้นทุนในการทำธุรกรรมได้เป็นอย่างดียกเว้นบางระดับนัยสำคัญสำหรับกลยุทธ์โมเมนตัมมาตรฐาน

ในท้ายที่สุด การศึกษานี้เผยให้เห็นว่าพอร์ตการลงทุนด้วยกลยุทธ์โมเมนตัมแสดงความไม่สมมาตรสำหรับความอ่อนไหวระหว่างตลาดกระทิงและตลาดหมี กลยุทธ์เหล่านี้มีแนวโน้มที่จะสร้างผลตอบแทนในเชิงบวกโดยสอดคล้องกับตลาดในช่วงขาขึ้น ในขณะเดียวกัน กลยุทธ์จะเคลื่อนไหวในทิศทางตรงกันข้ามกับช่วงตลาดขาลง โดนการลงทุนในพอร์ตการลงทุนด้วยกลยุทธ์โมเมนตัมในช่วงตลาดขาขึ้น นักลงทุนสามารถเพลิดเพลินไปกับกลยุทธ์การติดตามแนวโน้ม ในทางกลับกัน ระหว่างการกลับตัวของแนวโน้ม ความอ่อนไหวหรือความเสี่ยงจะลดลงโดยอัตโนมัติ ซึ่งความอ่อนไวที่ลดลงนี้ สามารถถูกตีความได้ว่าเป็นกลไกการจัดการความเสี่ยงโดยธรรมชาติที่มากับพอร์ตการลงทุนด้วยกลยุทธ์โมเมนตัม ตลอดทั้งช่วงเวลาในการศึกษานี้ กลยุทธ์โมเมนตัมแสดงให้เห็นถึงคุณลักษณะที่คงเส้นคงวา ยกเว้นในช่วงวิกฤตที่กลยุทธ์โมเมนตัมทั้งหมดมีความอ่อนไหวสูงมาก แต่อย่างไรก็ตาม ผลกระทบที่รุนแรงกับตลาดนี้เกิดจากการแพร่ระบาดทำให้เกิดการเปลี่ยนแปลงในคุณลักษณะของพอร์ตการลงทุนด้วยกลยุทธ์โมเมนตัม ซึ่งนำไปสู่การพังทลายของโมเมนตัมมาตรฐาน ก่อให้เกิดผลตอบแทนเชิงลบและความผันผวนที่เพิ่มสูงขึ้น

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต	
ปีการศึกษา	2565	ลายมือชื่อ อ.ที่ปรึกษาหลัก	

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KEYWORD: MOMENTUM STRATEGY, MARKET ANOMALIES, VOLATILITY-MANAGED PORTFOLIO, TIME-VARYING RISK

Chayakon Kamolsawat : The analysis of enhanced momentum strategies in the Stock Exchange of Thailand. Advisor: Assoc. Prof. ANIRUT PISEDTASALASAI, Ph.D.

The purpose of this study is to investigate the effectiveness of momentum strategies in investment portfolios, a well-known anomaly in the efficient market hypothesis, by portfolio are constructed by long winners and short losers. Specifically, the study focuses on the use of volatility to enhance momentum strategies in the Stock Exchange of Thailand from January 2013 to December 2022. The enhanced momentum strategies under investigation vary the portfolio weight with volatility and can be classified into constant volatility-scaled, constant semi-volatility-scaled, and dynamic-scaled approaches. The research aims to achieve two main objectives. Firstly, to analyze the potential of the enhanced momentum strategies by comparing the average return, the Sharpe ratio, and maximum drawdown, while also taking into account transaction costs as proxied by round-trip costs. Secondly, to examine the time-varying characteristics of these approaches and identify sub-periods within momentum crashes, which are associated with consistent negative returns. These periods typically occur during panic states following market declines and coincide with market rebounds. Additionally, asymmetry in bull and bear markets is analyzed.

The findings of this study demonstrate that enhanced momentum strategies exhibit superior performance compared to the standard momentum approach, both from a statistical and economic standpoint. These volatility-managed portfolios effectively scale and time the volatility of the standard portfolio, leading to improved returns and Sharpe ratio. Furthermore, the study highlights the emergence of a momentum crash in the Thai stock market, commencing in early 2020. Even amidst market crises such as the COVID-19 pandemic, certain enhanced strategies outperform the standard approach, particularly the dynamic approach. By considering the expected return in its scaling, this dynamic approach enables the portfolio to achieve high profitability during the momentum crash. Moreover, the study identifies that transaction costs are generally manageable, except for some significant levels observed in the standard momentum approach.

Finally, this study reveals that momentum portfolios display asymmetry in their sensitivity between bull and bear markets. These strategies tend to generate positive returns by aligning with the market during bullish phases, while moving in the opposite direction during bearish phases. By holding a momentum portfolio during a bullish market, investors can enjoy on the trend-following strategy. Conversely, during trend reversals, the sensitivity or risk automatically decreases. This decrease in sensitivity during trend reversals can be interpreted as an inherent risk management mechanism embedded within momentum portfolios. Throughout the sample period, these momentum strategies demonstrate a consistent characteristic, except during the crisis period. During this period, all momentum strategies exhibit significantly high sensitivity. However, the market's severe impact caused by the pandemic introduces changes in the characteristic of momentum portfolios, leading to a momentum crash and causing negative results and heightened volatility.

Field of Study:	Finance	Student's Signature ....
Academic Year:	2022	Advisor's Signature ....

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CHAPTER 1

Introduction

1.1 Background and Significance of the problem

The momentum strategy, initially posited by Jegadeesh and Titman (1993, 2001), proposed that purchasing stocks that have achieved greatly through the preceding six months (defined as winners) and short-selling those that have underperformed (defined as losers) can result in consistent abnormal returns when used for a three to twelve months holding period. This tactic challenged the well-established efficient market concept introduced by Fama (1970), as this momentum is the anomalies in this market hypothesis or could be potentially interpret as inefficient in the market. The effect of momentum is not limited to U.S. stocks, but research has shown that this profit-generating strategy is also applicable to a variety of samples. Asness et al. (2013), for instance, showed how different economies and alternative investments are impacted by momentum. Additionally, Chui et al. (2000) and Chiao et al. (2020) found high profits when implementing this method of acquiring prior winners and short-selling prior losers in Asian countries, except Japan. So, Butt et al. (2021) investigated further by using samples in emerging markets and found lower profits. Rouwenhorst (1998) observed similar results in European countries, and Griffin et al. (2003) extended this idea globally.

Many researchers have attempted to find an explanation for why momentum strategies can consistently generate profits. Interestingly, Fama and French (1996) proposed the Fama-French three factors model (FF3FM) to rationalize the continuation of returns, but it was not entirely successful. Carhart (1997) later improved the model with the addition of a fourth factor, but it still did not fully explain the phenomenon, which these risk factors could be the respond that show efficiency in the market. However, as Jegadeesh and Titman (2001), risk-based theories were not sufficient to explain the long-term reversal of the momentum effect. In order to understand the prevalence of momentum profits, it is necessary to focus on investors' behavioral biases. Jegadeesh and Titman (1993) suggested that momentum was caused by investors' inefficient reaction to new information.

However, it should be noted that positive returns from momentum strategies are not always guaranteed, and occasional crashes can occur. The characteristic of currency samples, as demonstrated by Brunnermeier et al. (2008), was negatively skewed. Additionally, Grundy and Martin (2015) proposed that the time-varying property of market beta was a risk associated with momentum strategies. For example, when the market experiences a dramatic rebound following a bear market, the portfolio of losers tends to rebound faster than the portfolio of winners, resulting in a negative return for the overall winner-minus-loser strategy during that period. Asem and Tian (2010) investigated the interaction terms when the market was in a transition period, such as when the market moved downward and subsequently upward.

In addressing the problem of momentum crashes, volatility-scaled momentum strategies have been proposed. Barroso and Santa-Clara (2015) proposed scaling the strategy to have constant volatility. Similar to Wang and Yan (2021), they distinguished between downward and upward movements and scaled by downside volatility. Additionally, Daniel and Moskowitz (2016) improved the scaling by incorporating the expected return of the strategy. These literatures relate to volatility enhancement in momentum strategies. By incorporating past return or volatility in enhancement, when the past volatility is high, these portfolios tend to reduce their investment weight as they intend to reduce their risk exposure. In contrast, when its past volatility is low, these portfolios tend to add up more weight in order to increase its return. Addition to these volatility enhancement, Frazzini and Pedersen (2014) suggest low volatility anomalies which suggest that low beta stocks tend to outperform the others, which their strategies seek to identify stocks with lower systematic risk or volatility than the broader market. This study focus on capturing the stocks that have tendency to continue their strong positive performance and assume that the trend will persist instead of the smooth return profile. Also, these volatility enhanced strategies are not only less expose to the crisis but also utilize the crisis in improvement their strategies.

Since there are also various ways to evaluate the performance of each strategy which this study uses benchmark of portfolio as the Sharpe ratio introduced by Sharpe (1998) for practically understanding and simplicity in comparison, while this benchmark could be improved further from its estimation accuracy as suggested by Lo (2002) that the Sharpe ratio could be adjust by their return generating investment style. Furthermore, this comparison of Sharpe ratio could be refined according to research of Wright et al. (2014) by incorporate more general assumptions related to their investment returns distribution in order to compare equally. Then, Hanauer and Windmüller (2023) compared enhanced momentum strategies by examining returns, variance, and higher moments as proposed by Barillas et al. (2020) and by determining the break-even cost based on the methods proposed by Asness and Frazzini (2011), Grundy and Martin (2015), Barroso and Santa-Clara (2015), Moreira and Muir (2017) and Gibbons et al. (1989).

According to the literature, momentum investing is a strategy that involves taking a long position in stocks that exhibit good performance and a short position in stocks that present bad performance, which generates consistently positive returns throughout the period. Despite some periods of anomalies, or in literature, called momentum crashes period, where this strategy generates negative returns, these periods usually happen after the crisis in which past poor performers generate more returns than the others. These crashes usually occur during the market transitions when the market moves upward, followed by a bear market, or the market move downward, followed by a bull market. Therefore, the enhanced momentum strategies aim to manage these crashes by scaling the strategies with volatility. The idea is based on the empirical evidence that return has a negative correlation with volatility. That is, the return is high when the volatility is low.

This study compares the performance of these three volatility-scaled momentum strategies from pieces of literature in the Stock exchange of Thailand using a long sample of the data, then determines the minimum returns that these strategies should generate to be considered as investment options. Additionally, analyzing of time-varying behavior is conducted using sub-period around the crisis period, such as the COVID-19 pandemic and during bear and bull market conditions. Therefore, this study aims to fill the gap in the literature related to momentum strategies using data in the Thai market, which is primarily influenced by the energy sector and experiences high volatility. This study significantly contributes to the academic field in at least two aspects. Firstly, it expands the limited empirical evidence from previous literature on momentum strategies, which mainly shed light on the U.S. and other developed markets, by providing valuable insights into the Thai stock market characteristics. Secondly, this study provides an evaluation of the returns, volatility, skewness, and kurtosis of the standard momentum portfolio and the performance of each enhanced strategy in the Thai market and also explores the potential of these strategies for implementation in the Stock Exchange of Thailand. Additionally, this study contributes to the academic theories in field of finance in aspects of market efficiency and asset pricing model. As momentum effect will be shown throughout the period, it proves the market is not actually efficient in the Thai stocks market. Moreover, this study provides additional information for conducting asset pricing model which relates directly to pure momentum such as four factors model, and helps in improvement of asset pricing model in considering the volatility in enhancing the momentum strategies.

This paper also has practical implications for investors and fund managers, especially for active portfolio management, as momentum investing is implemented in the market instead of tracking the index as conducted by the passive portfolio management. This study provides insights into the performance of various momentum strategies in the Thai stock market, offering guidance on how to best utilize these strategies and identifying effective methods for scaling momentum strategies to minimize crashes. Additionally, it suggests stock selection process in order to be applicable with the momentum investing strategies, and guides rebalancing period which practically utilized in the previous literature. Moreover, this research highlights potential risks associated with momentum investing, which can inform or aid in the creation of policies by policy makers, such as preventing short-squeezing or regulating short-selling activities. Furthermore, it provides guidance on how to measure the performance of momentum strategies, allowing fund managers to make more informed investment decisions.

The proposal's remaining sections are organized as follows: In Section 2, the relevant literature is reviewed. The data, factor building, and improved momentum procedures are all described in Section 3. The study technique is shown in Section 4.

1.2 Objectives

This study's main objectives are to analyze the possibilities for using momentum methods and to take a glance at the time-varying features of the Thai Stock Exchange. Two distinct goals are the goals of the investigation.

Comparing the performance of various volatility-scaled momentum methods is the first goal, such as constant volatility-scaled momentum (cMOM), constant semi-volatility-scaled momentum (sMOM), and dynamic-scaled momentum (dMOM), against the standard momentum strategy. The goal is to determine whether there is an abnormal return or better performance in the long run while taking transaction costs into account in order to evaluate the minimum profit that the strategies must generate to be considered a practical investment option.

Examining the time-varying behavior of momentum techniques is the study's second goal. In order to accomplish this, the study will take two steps. The first step will involve studying the behavior of each strategy before, during, and after crises, with a focus on the momentum crashes. For example, it is often observed that losers perform better than winners after crises. In the second step, the study will dig deeper into the study of the behavior of each strategy in bull-up and bear-down markets. Some strategies may not outperform the standard momentum strategy in all market conditions, but this may change during bull-up periods, or they may outperform in all conditions, as demonstrated in many studies of the US market. Thus, it is important to carefully consider the results of this study before making investment decisions.

1.3 Research Hypothesis

Hypothesis 1.a: *The volatility-managed momentum approaches will provide abnormal returns compared to standard momentum methods.*

The rationale behind this hypothesis is that during abnormal market conditions, this paper is poised to assign greater significance to stocks that exhibit exceptional performance while allocating lesser importance to underperforming stocks. Several scholarly works have proposed augmenting the standard momentum strategy, particularly in relation to volatility. Specifically, Barroso and Santa-Clara (2015) effectively managed risk and thus achieved an almost twofold increase in risk-adjusted returns. Similarly, Wang and Yan (2021) enhanced performance by incorporating downside volatility for substituting the total volatility, whereas Daniel and Moskowitz (2016) employed a momentum crash scaling technique, both of which demonstrated significantly superior performance. The conventional momentum procedure and volatility-scaled momentum methods were compared using emerging market samples by Hanauer and Windmüller (2023), who found that all enhanced momentum approaches outperformed the standard strategy in return and risk-adjusted return aspects.

Hypothesis 1.b: *After taking into account transaction cost, the enhanced momentum strategies should generate profit.*

This study emphasizes the crucial aspect of ensuring the practical implementation of each strategy, where the generated returns must outweigh the transaction costs involved. The underlying hypothesis stems from the fundamental principle that investment decisions should only be undertaken when the anticipated returns surpass the expenses associated with executing the trades. Scholars such as Grundy and Martin (2015) and Barroso and Santa-Clara (2015) have proposed a method to calculate a proxy for transaction costs based on the turnover of stocks within each momentum portfolio, considering the significance of the portfolios' return. Hanauer and Windmüller (2023) further contributed to this area by implementing transaction costs in both U.S. and world ex-U.S. contexts, utilizing a lengthy sample period. The findings of this study highlight the promising potential for implementing a volatility-managed portfolio approach in a general setting.

Hypothesis 2.a: *The standard momentum should generate negative outcomes, and the volatility-scaled momentum strategies should generate less negative or potentially generate positive returns during the COVID-19 pandemic.*

Daniel and Moskowitz (2016) meticulously explored the anomalies inherent in momentum strategies and revealed a notable phenomenon wherein the traditional momentum portfolio experiences negative returns during periods characterized by momentum crashes. These crashes typically transpire subsequent to crises that profoundly impact stock markets and investor sentiment. Empirical evidence consistently suggests that the standard momentum approach is susceptible to market crashes. However, the introduction of volatility-scaled momentum strategies, as elucidated in numerous prior studies, holds the promise of exhibiting superior performance compared to the standard momentum portfolio. For instance, Wang and Yan (2021) implemented their strategy using a U.S. sample and meticulously documented its notable outperformance relative to the standard portfolio.

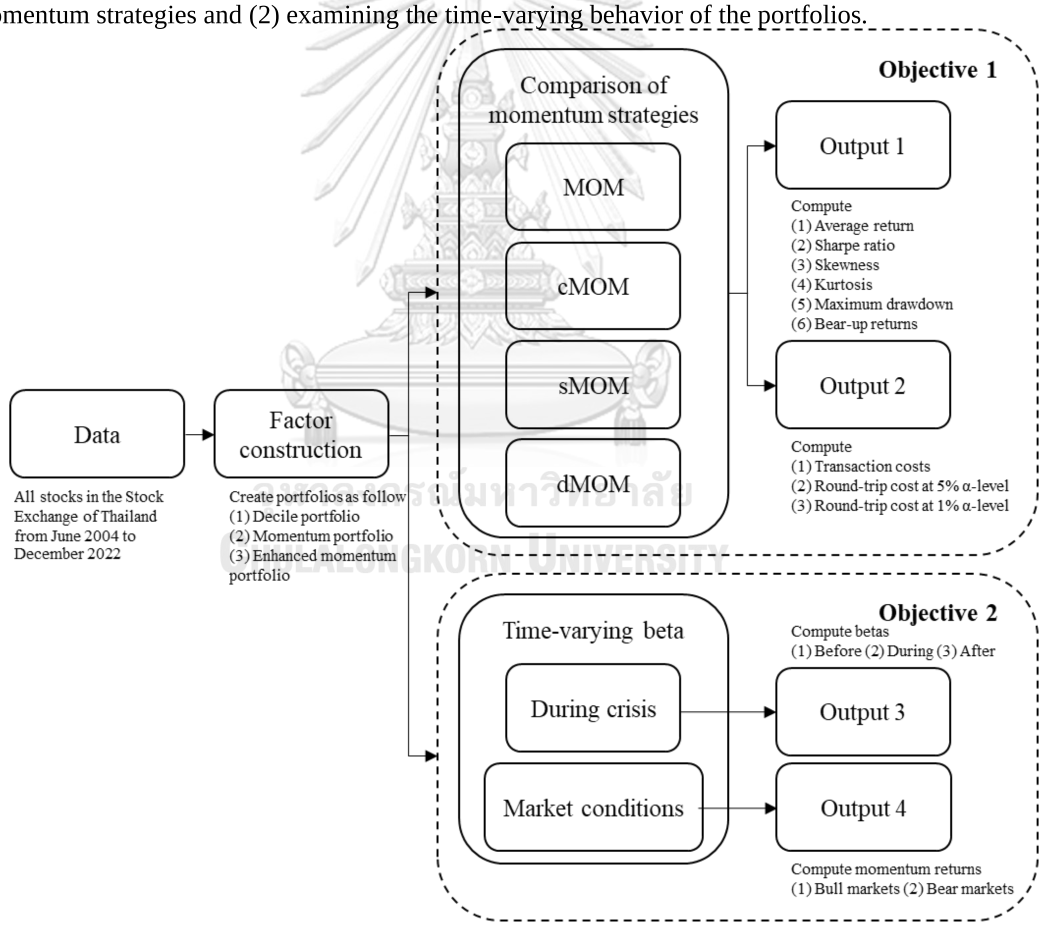
Hypothesis 2.b: *The momentum strategies, including both standard and volatility-scaled variants, should exhibit consistent performance across a range of market conditions.*

Consistency plays a pivotal role in guiding investment decision-making as practitioners strive to identify strategies that demonstrate robustness and remain resilient in the face of market volatility. Investors have a legitimate rationale for anticipating that their investment strategies exhibit consistency, thereby enabling them to effectively enjoy trend-following strategies. Additionally, Daniel and Moskowitz (2016) conducted an in-depth analysis of individual securities in the U.S. and revealed a noteworthy asymmetry between bull and bear market states. Particularly, during bullish market conditions, the statistical significance of the sensitivity effect was found to be insignificant, but overall, the performance is well consistence.

1.4 Conceptual Framework

This study will follow a comprehensive research methodology as outlined in the conceptual framework. The first step will involve collecting relevant data from reliable sources. Following this, the construction of momentum portfolios will be carried out with the aim of achieving two main objectives: (1) comparing the performance of various momentum strategies and (2) examining the overtime attitudes of the portfolios.

Figure 1 This diagram shows the conceptual framework of this study.
The figure above shows the conceptual framework of this study which start from the input data, and then factor was constructed to put in these two objectives: (1) comparing the performance of various momentum strategies and (2) examining the time-varying behavior of the portfolios.



CHAPTER 2
Literature review

Concept and Theory

In this study examining the potential for utilizing momentum strategies and the time-varying characteristics in the Stock Exchange of Thailand, the conceptual framework will be anchored in the efficient market hypothesis, momentum strategy, and momentum crashes.

According to the efficient market hypothesis, since asset prices already account for all available information, it is difficult to generate persistently anomalous returns in the financial markets. Given that the market is thought to be efficient, this means that the traditional momentum approach would not be able to produce excess returns over the long term.

Momentum strategies, on the other hand, involve investing in securities that have shown recent positive performance while avoiding those that have exhibited negative performance. The theory behind momentum strategies is rooted in the phenomenon of momentum persistence, which posits that securities that have performed well in the past are likely to continue to perform well in the future. However, there are instances where the standard winner-minus-loser portfolios result in consistently negative returns, a phenomenon referred to as momentum crashes. These events often occur during crisis periods, such as the 2000s housing bubble crisis and the global financial crisis, among others.

Relevant research

In this section, this paper is going to present a summary of relevant papers (1) Efficient market hypothesis, (2) Momentum strategy, (3) Enhanced momentum approaches, (4) Momentum crashes, and (5) Volatility-scaled momentum strategies.

Efficient market hypothesis

Fama (1970, 1995, 1998); Fama and French (1993) have made significant contributions to the field of finance through their works with the efficient market hypothesis (EMH). He provided a comprehensive overview of the EMH and its implications for capital market efficiency, including the argument that it is impossible for investors to consistently identify mispriced securities as prices of securities should accurately and instantaneously represent all accessible data. As a consequence, even active fund managers are expected to only earn normal profits that compensate for the underlying risk of stocks. The implications of the EMH extend to investors, fund managers, corporate management, and regulators. However, they have also acknowledged the limitations of the EMH, arguing that it fails to account for the role of behavioral factors in stock market prices and that market inefficiencies can result from the actions of rational but fallible investors.

Momentum strategy

Following hypothesis testing, Fama (1970) came to the conclusion that there are many types of market efficiency, including weak form, semi-strong form, and strong form efficiency. He then reviews the evidence in favor of or against each type of efficiency. His famous weak-form test for the efficient market hypothesis asserts that stock prices already reflect all information found in market trading data, such as price movements and trading volumes, and that, therefore, trading strategies based on technical analysis will not typically produce abnormal returns.

However, Jegadeesh and Titman (1993) challenged this view with their idea that portfolios of stocks that have generated strong performance through the previous stage seem to be more likely to do so in the future. The authors argued that if there is evidence of over- or under-reaction to new information in the market, then an investment strategy that chooses companies according to their preceding performance can be profitable. This strategy, known as the J-month/K-month method, involves ranking stocks based on their past returns over J months and holding them for K months. Using data from the NYSE and

AMEX, Jegadeesh and Titman (1993) showed that this approach can generate approximately 1.3% monthly returns and even more profit with some adjustments to the strategy, demonstrating a momentum implication for the U.S. stock exchange.

Enhanced momentum approaches

Extensive research in the field of momentum investing has yielded numerous improvements, as documented in the literature. These improvements encompass various aspects such as industry momentum, volatility integration, time-series momentum, momentum crashes, and behavioral momentum.

Moskowitz and Grinblatt (1999) argue that industry effects could be an explanation for size and book-to-market effects as well. So, they researched the U.S. common stocks ranging from July 1963 to July 1995. Their study found that Momentum is not solely a cross-sectional phenomenon. Momentum strategies performed robustly at the industry level. The results suggested that a strategy of buying stocks from past winning industries and selling stocks from past losing industries could achieve significant abnormal returns.

Barroso and Santa-Clara (2015) inspected the U.S. stocks from July 1926 to December. They proposed that momentum strategies have higher expected returns but also higher risk. By scaling exposure to the momentum strategy using a dynamic volatility model, risk-adjusted returns can be significantly improved. This approach is particularly effective in avoiding large losses during momentum crashes.

Moskowitz et al. (2012) considered Various asset classes, including commodities, currencies, equity indices, bonds, and individual U.S. stocks, spanning more than a century for some asset classes from many markets around the world. They found that a strategy that goes long past winners and past short losers generates a significant positive return in every asset class-tested. Time-series momentum is a pervasive phenomenon and can be a profitable strategy across different markets and asset classes. Also, Time-series momentum strategies may offer diversification benefits when combined with traditional asset allocation strategies.

Daniel and Moskowitz (2016) proposed that a strategy that reduces exposure to momentum during momentum crash periods can significantly mitigate crash risk, as Momentum strategies are prone to occasional large crashes. These crashes are predictable and tend to occur in periods following market declines and when market volatility is high. They researched U.S. stocks from 1927 to 2013 and came up with a strategy that effectively managed this momentum crash and yielded great results.

Hong and Stein (1999) proposed a model that unifies the phenomena of momentum and overreaction based on assumptions about investor behavior and information diffusion. The model predicts that underreaction to information leads to momentum, and delayed overreaction leads to a reversal. While the paper doesn't provide empirical evidence, it offers a theoretical foundation for momentum and reversal phenomena in asset markets based on behavioral economics.

Momentum crashes

Daniel and Moskowitz (2016) introduced the idea of momentum crashes, which are periods where losers outperform winners, leading to significant negative returns for momentum portfolios. They analyzed the impact and potential of these crashes, finding that they typically occur during market panics, characterized by high volatility and steep drops in market returns.

This phenomenon has also been observed in the currency market, as demonstrated by Brunnermeier et al. (2008) in their study of carry trade strategies. They argue that the high returns to the carry trade strategy can be viewed as a risk premium for the exposure to these crash risks. They also find that funding liquidity plays a role in the carry trade strategy, where a decrease in funding liquidity predicts an increase in the price of risk. So, they investigated exchange rates, interest rates, and stock indices from developed and emerging markets from 1986 to 2006 and found the link between the carry trade strategy (borrowing in low-interest-rate currencies and investing in high-interest-rate currencies) and the risk of currency crashes. They found that carry trades often unwind during global crises, leading to 'carry crash' risk.

The findings of Cooper et al. (2004) are consistent with these results, suggesting that the momentum premium becomes negative during periods of high volatility. They argue that their findings are consistent with the gradual information diffusion hypothesis, where the market slowly incorporates information into stock prices, and this process depends on the market state. They worked on the U.S. stocks from January 1926 to December 1995 and found that the momentum strategy works well in up markets but not in down markets. In other words, the performance of momentum strategies is conditioned on the state of the market. Stocks with high past returns continue to perform well in the future in up markets, but the pattern is reversed in down markets.

In response, Daniel and Moskowitz (2016) proposed a dynamic-scaled momentum strategy, which adjusts the weights of the winner-minus-loser portfolio over time based on their performance during rebalancing periods. This new approach demonstrates remarkable robustness across time periods and asset classes.

Volatility-scaled momentum strategies

The improvement of momentum strategies by utilizing the volatility of its returns has been a topic of interest among practitioners and researchers after the 2000s century. For the purpose of achieving this goal, various methods have been proposed to generate higher returns or lower volatility, especially for some enhanced momentum strategies that are constructed to tackle momentum crashes.

Barroso and Santa-Clara (2015) introduced the constant volatility-scaled momentum (cMOM) strategy, which adjusts momentum returns based on a forecasted variance. They explored the U.S. stock from July 1926 to December 2012 and argued that the momentum strategy is exposed to episodic drawdowns (crashes) and suggested a volatility-scaled momentum strategy, which scales down the size of positions in times of high forecasted volatility.

The volatility-managed momentum strategy performs better on a risk-adjusted basis and has smaller drawdowns.

Wang and Yan (2021) further improved this approach by incorporating downside volatility in their scaling, resulting in the constant semi-volatility-scaled momentum (sMOM) strategy. They examined the U.S. individual stocks, industry portfolios, and international stock market indices from August 1926 to December 2018 and found that volatility-managed portfolios help in mitigating downside risk in investments. This is consistent across individual stocks, industry portfolios, and international stock market indices. The downside risk is predictive of the performance of volatility-managed portfolios, and they also suggest that investors seeking to manage downside risk should consider volatility-managed strategies.

Another approach is the dynamic-scaled momentum (dMOM) strategy proposed by Daniel and Moskowitz (2016), which includes a forecast of momentum returns in the scaling process. Since they observed the U.S. common stocks from 1927 to 2013 and found that momentum strategies are prone to occasional large crashes, they suggested that these crashes are predictable and tend to occur in periods following market declines and when market volatility is high.

A comparison of these momentum strategies was conducted by Hanauer and Windmüller (2023). They came up with the question that whether the volatility-managed momentum strategies outperform the standard momentum approach or not in the aspect of the Shape ratio. Therefore, they studied from a very long sample of the U.S. data (approximately 100 years) and the other countries as well but with a shorter sample period. They are one of the researchers who showed that these approaches not only reduce momentum anomalies but also result in higher risk-adjusted returns when measured by various methods, including those proposed by Barillas et al. (2020), Grundy and Martin (2015), Barroso and Santa-Clara (2015), Moreira and Muir (2017), and Gibbons et al. (1989). They noticed that enhanced momentum strategies that take into account more than just past returns can outperform traditional momentum strategies and also suggests that investors can potentially increase the profitability of momentum strategies by considering additional company and market information. These can include factors such as firm size, valuation ratios, and other financial indicators.

Additionally, Grundy and Martin (2015) offered the performance-controlled transaction cost that is not normally analyzed in investing strategies research. They considered the U.S. stocks from 1926 to 1995 and found that momentum profits are not primarily the result of systematic risk or behavioral bias and also suggest that there might be a state variable that is relevant to both the momentum strategy's performance and the stock market's conditions. The strategy exhibits large systematic fluctuations in performance, suggesting a time-varying risk premium.

Since this study compare all momentum strategies together in many aspects, there are also various ways of measurement dynamic volatility that could be the volatility model such as GARCH model introduced by Engle (1982) or realized volatility which estimate and forecast the volatility by the model which need assumptions that the volatility is time-varying and depends on recent past values of returns, past volatility, and the order that might vary among the period of consideration. While rolling estimated volatility are conducted in this paper according to the simplicity and more conventional way of measurement the volatility when comparing with the other methods. Additionally, these practices could be referred to the literature related to volatility-enhanced momentum strategies that prevailing use the rolling estimate methods in their strategies improvement. Moreover, the other aspect that could be measured is the dynamic beta which can be captured by a well-known method in econometric introduced by Bauwens et al. (2006) as multivariate GARCH (M-GARCH) model. Raddant and Wagner (2022) applied this model and showed that even their model has low parameter number, but with the right relationship, this model can show better in accuracy.

In consideration of the performance characteristic as proposed by Daniel and Moskowitz (2016), their regression equations focus separately between bull and bear market conditions which they have to incorporate the dummy variable which can be called bear indicator in order to identify these two market conditions. Since this study utilize bear indicator referring to the previous literature, there are prevailing ways in defining this bear indicator that are Markov-switching suggested by Kim (1994) who suggest the model that allows for shifts or changes in the parameters of a statistical model based on an underlying unobserved state variable, threshold model suggested by Caner and Hansen (2004) that accounts for nonlinearity in the relationship between variables or when the specific threshold level is present, and smooth transition regression introduced by Gonzalez et al. (2017) who extend the linear regression model by allowing the coefficient to vary through both cross-section and time. Since these practices have their own pros, cons, and more assumptions are needed which arguably discuss by previous literature, the study stick on conventional ways of identifying the trend of the market as utilized the market past return as the indicator.

CHAPTER 3
Data

3.1 Data

This study focuses on the performance and characteristics of the momentum strategy during the COVID-19 pandemic period. To ensure that the pandemic period is not contaminated by other crises, the observation period is selected from January 2013 to December 2022. The starting period of 2013 was chosen due to the hamburger or subprime mortgage crisis in 2008 and the Thailand flood crisis in 2011. Therefore, this research utilizes daily and monthly total return indices, trading volume, common shares outstanding, and market capitalization data for all stocks listed on the Stock Exchange of Thailand during the period of January 2013 to December 2022. These data were obtained from Refinitiv Datastream, and the monthly total return index of the SET index was obtained from the same source. Additionally, monthly yield data for a one-month Thai treasury bill was obtained from the Bloomberg terminal. A list of data explanations used in this study is provided below.

1. The total return index of all stocks in the Stock Exchange of Thailand is used as a proxy for stock price because it shows a theoretical growth in value over a specific period that is to capture gains from both dividend and capital, also adjusted price and adjusted number of shares outstanding from splitting into shares and shares buying back.
2. The market capitalization of all stocks is used as a proxy to define size breakpoints for non-U.S. samples following Fama and French (2012, 2017).
3. Monthly data of the total return index of a SET index is used as a proxy for the market return index, which is a value-weighted index of all stocks weighted according to the total market value of their outstanding shares.
4. Monthly data for the yield of a one-month Thai treasury bill is used as a proxy for a risk-free rate.

In order to ensure the accuracy of the results and minimize the impact of bid-ask bounce on thinly traded securities, this study omits stocks that have a share turnover below 0.01%. Share turnover is calculated as the ratio of the total shares traded over a given period to the average shares outstanding during that period.

$$Shares\ turnover_{i,t} = \frac{Trading\ volume_{i,t}}{Average\ Share\ Outstanding_{i,t}} \tag{1}$$

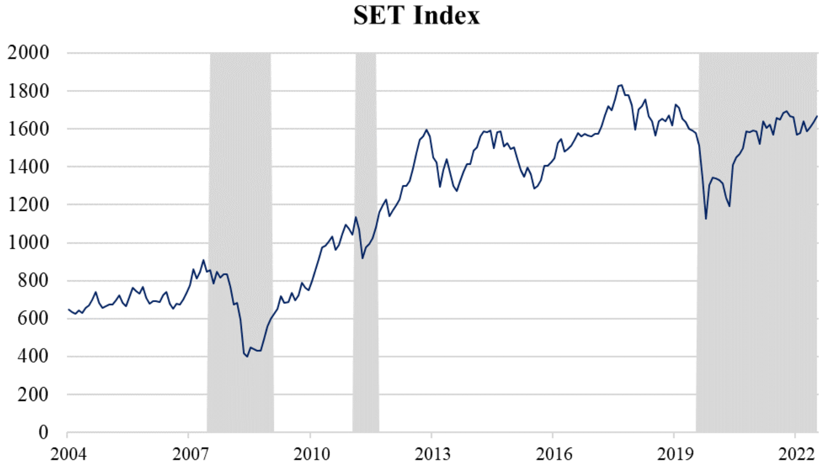
where $Trading\ volume_{i,t}$ is the average daily trading volume of stock i at time t and $Average\ Share\ Outstanding_{i,t}$ are average shares outstanding of stock i at time t.

3.2 Momentum crashes

Momentum crash periods are the periods of anomalies in investment strategies in which they significantly underperform and generate consistently negative returns. It usually occurred during crises when the market was panicked, which created high volatility, followed by the market pullback, and these strategies came with substantial, sustained losses. This study will provide an illustration of the returns for the winner-minus-loser (WML) portfolios and market return. The results provide a comprehensive summary of the correlation between the period in which the winner-minus-loser portfolio generates negative returns and the market return and lagged return.

Additionally, Figure 2 illustrates the Stock Exchange of Thailand index, highlighting the gray-shaded areas that represent significant crisis periods that have profoundly impacted the Thai market. These crises include the global financial crisis depicted on the left side, the 2011 Thailand flood in the middle, and the far right-hand-side crisis, which corresponds to the COVID-19 pandemic, the primary focus of this study. During these critical periods, the SET index exhibits distinct characteristics that align with the definition of a momentum crash, wherein the market experiences a substantial decline followed by a sharp rebound. As a result, investigating the performance of momentum strategies within these crisis periods becomes particularly intriguing.

Figure 2 The SET index.
This Line chart shows the Stock Exchange of Thailand index with the gray-shaded area is the crisis which significantly impacts the Thai market.

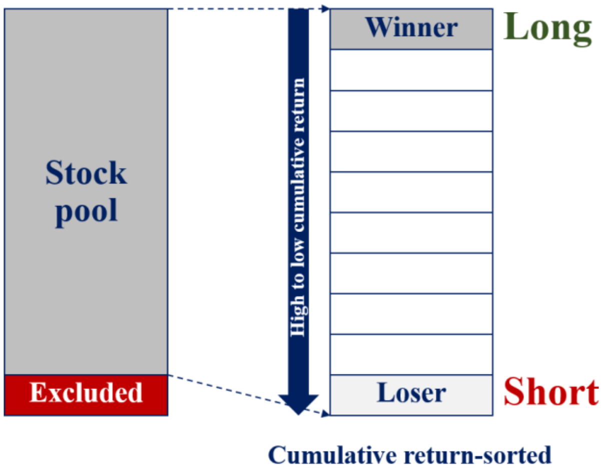


3.3 Traditional momentum portfolio

This traditional momentum portfolio can be viewed as a decile winner-minus-loser (WML) portfolio. In order to ensure the validity of the results in this study, strict criteria must be imposed on the stock selection process. Only stocks with a valid share price and number of shares as of the formation date will be considered for the analysis. This requirement helps eliminate any potential errors in calculation due to missing data. Stocks that do not meet these criteria will be excluded from the stock pool.

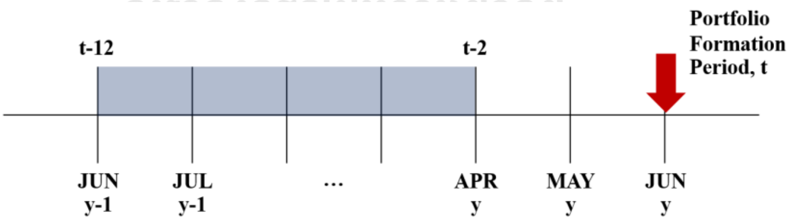
The stocks that meet the criteria will then be sorted into ten decile portfolios, with the first portfolio representing the lowest performers or defined as losers and the tenth representing the highest performers, as depicted in Figure 3.

Figure 3 The procedure of forming a portfolio using cumulative return-sorted.
The figure above shows an example of how the traditional momentum portfolio. The stocks are excluded if the share turnover is below the criteria of 0.01% annually. Then, stocks are sorted by their past cumulative return from month t-12 to month t-2, and portfolios are constructed as the first decile portfolio (defined as a loser) and the tenth decile portfolio (defined as a winner).



To form the momentum portfolio, the period of consideration is 12 months leading up to the formation date, as demonstrated in Figure 4. Additionally, the ranking of the stocks will be based on their performance over this period, and the portfolios will be rebalanced at the end of each month.

Figure 4 Example of the period for calculating cumulative return.
The figure above shows the time period for calculating the cumulative return from 12 months before to one month before the formation date.



3.4 Data descriptive

Section 3.4 provides a comprehensive overview of the summary statistics utilized in this study, covering the period from January 2013 to December 2022. The data used for analysis and interpretation plays a critical role in ensuring the validity and reliability of the research findings.

Beginning with the summary of descriptive statistics presented in table 1, this table showcases the return statistics of each component of the standard momentum portfolio. These components are the Big-Winner portfolio (referred to as BW), Big-Loser portfolio (referred to as BL), Small-Winner portfolio (referred to as SW), and Small-Loser portfolio (referred to as SL). The returns of these portfolios are essential in computing the return of the standard momentum, which will serve as the foundation for calculating enhanced momentum strategies.

Table 1 reveals the returns of these portfolios over a total of 120 months. The average monthly raw returns are computed as follows: 0.66% (equivalent to 7.92% per year), 0.47% (equivalent to 5.64% per year), 0.84% (equivalent to 10.08% per year), and 1.44% (equivalent to 17.28% per year) for BW, BL, SW, and SL, respectively. Furthermore, the monthly standard deviations are determined to be 5.46%, 5.76%, 6.13%, and 7.35% for BW, BL, SW, and SL, respectively.

Additionally, the average monthly value-weighted returns are calculated as 0.71% (equivalent to 8.52% per year), 0.60% (equivalent to 7.20% per year), 0.56% (equivalent to 6.72% per year), and 0.82% (equivalent to 9.84% per year) for BW, BL, SW, and SL, respectively. The corresponding monthly standard deviations for these portfolios are 5.20%, 5.68%, 5.80%, and 7.09%, respectively.

By presenting these summary statistics, this study provides valuable insights into the performance and characteristics of the various components within the standard momentum portfolio. These statistics serve as a foundation for further analysis and the development of enhanced momentum strategies.

For portfolios of big stocks, both BW and BL generate higher raw returns than the value-weighted return, indicating that heavily invested stocks outperform stocks that are less invested. These big stock portfolios not only generate higher value-weighted returns but also have a lower standard deviation, which is known as the "diversification benefit" in financial theory. In contrast, for portfolios of small stocks, both SW and SL generate lower raw returns than the value-weighted return, indicating that these strategies invest more in stocks that underperform relative to stocks that are less invested. These small stock portfolios generate lower value-weighted returns and standard deviation, which is known as a "trade-off" in financial theory. When constructing the momentum portfolio, its return shows a lower standard deviation than the market as it is a long-short investing strategy, which is safer than a one-way investment.

Table 1 Summary of descriptive statistics.

The table below presents the following descriptive statistic for monthly returns of the components of the standard momentum portfolio (1. Big-Winner portfolio (BW), 2. Big-Loser portfolio (BL), 3. Small-Winner (SW), and 4. Small-Loser (SL)) and the SET index which including (1) Count or the number of months in this sample period, (2) Mean or average return, (3) Max, (4) Min, (5) Median, and (6) Standard deviation.

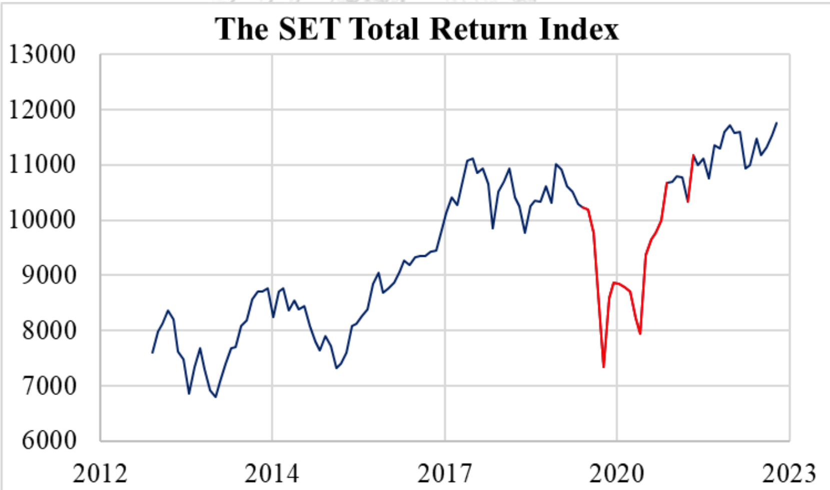
	2013-2022	**Monthly**					
		Count	**Mean**	**Max**	**Min**	**Median**	**SD**
Raw Return	**BW**	120	0.66%	21.90%	-17.66%	0.79%	5.46%
	BL	120	0.47%	27.23%	-17.39%	0.29%	5.76%
	SW	120	0.84%	24.80%	-20.15%	1.10%	6.13%
	SL	120	1.44%	34.15%	-19.72%	1.10%	7.35%
VW Return	**BW**	120	0.71%	22.37%	-15.83%	0.81%	5.20%
	BL	120	0.60%	30.21%	-19.82%	0.61%	5.68%
	SW	120	0.56%	20.09%	-18.42%	0.56%	5.80%
	SL	120	0.82%	30.75%	-24.89%	1.00%	7.09%
	MOM	120	-0.08%	9.90%	-17.87%	0.29%	3.56%
	SET	120	0.51%	17.99%	-15.46%	0.64%	4.44%

Continuing with Figure 6, the presented line graph depicts the SET total return index, with the red-colored section in the graph representing the bear market periods of the SET index. These bear market conditions are determined by the bear market indicator ($I_{Bear,t-1}$), following the methodology recommended by Daniel and Moskowitz (2016). According to this approach, a negative cumulative market return over the past two years indicates a bearish trend in the market, and consequently, the bear market indicator assumes a value of 1. Conversely, if the 2-year cumulative market return is positive, the bear market indicator assumes a value of zero. This indicator proves valuable when examining the asymmetric return of momentum strategies during bullish and bearish market trends.

Furthermore, this indicator is an indication of the overall health of the economy, as a positive market return is often associated with positive economic indicators such as strong GDP growth, low unemployment, and low inflation. When the economy is performing well, companies tend to do better, which can increase investor confidence and drive-up stock prices. It is noteworthy that, in the Thai stock market, the bear market indicator has been zero for less than 20% (20 months out of the total 120 months of the study periods) of the observation period, indicating that the SET index mostly goes up.

It is important to note that most of the bear market states in the Thai stock market occurred around the COVID-19 pandemic, which had a significant impact on the global economy. The pandemic resulted in widespread lockdowns, travel restrictions, and reduced economic activity, which caused many companies to struggle and led to a sharp decline in stock prices. However, despite the challenges posed by the pandemic, the Thai stock market has shown resilience and has rebounded strongly in the aftermath of the pandemic.

Figure 5 The SET total return index.
The figure above demonstrates the line chart of the SET total return index from January 2013 to December 2022, and the red color in the line chart shows the bearish trend in the market as its past two years' cumulative return is below zero.



Tables 2 and 3 demonstrate notable differences in the covariance between raw returns and value-weighted returns of the four components of the standard momentum portfolio to the market return. The momentum portfolio components (BW, BL, SW, and SL) exhibit covariances of raw returns at 88%, 92%, 84%, and 77%, respectively, whereas the covariances of value-weighted returns are found to be 88%, 90%, 83%, and 86% respectively.

A value-weighted portfolio weights stocks by their market capitalization, resulting in larger companies having a more significant impact on the portfolio's returns. Conversely, a raw returns portfolio gives equal weight to each stock, irrespective of its size. Therefore, when the market is performing well, the value-weighted portfolio is heavily influenced by the large-cap stocks leading the portfolio, leading to a high correlation with market returns.

Remarkably, the raw returns portfolio distributes returns more evenly across all stocks, resulting in a correlation with market returns similar to that of the value-weighted portfolio, with the exception of the Small-Loser portfolio (SL), which exhibits a 10% lower covariance at 77% with market returns, yet remains relatively high.

Table 2 Variance and covariance matrix of raw returns and the market returns.
The table below shows the variance-Covariance matrix between raw returns of the components of the momentum portfolio, i.e., Big-Winner (BW), Big-Loser (BL), Small-Winner (SW), and Small-Loser (SL), and returns of the SET index.

	BW	BL	SW	SL	SET
BW	100%				
BL	77%	100%			
SW	86%	75%	100%		
SL	70%	77%	85%	100%	
SET	88%	92%	84%	77%	100%

Table 3 Variance-covariance matrix of value-weighted returns and the market returns.
The table below shows the variance-Covariance matrix between value-weighted returns of the components of the standard momentum portfolio, i.e., Big-Winner (BW), Big-Loser (BL), Small-Winner (SW), and Small-Loser (SL) and returns of the SET index.

	BW	BL	SW	SL	SET
BW	100%				
BL	67%	100%			
SW	80%	67%	100%		
SL	70%	79%	85%	100%	
SET	88%	90%	83%	86%	100%

CHAPTER 4
Methodology

4.1 Factor construction

4.1.1 Standard momentum strategy

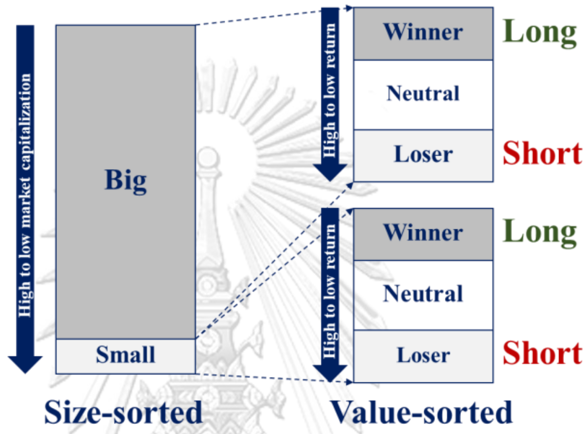
In this study, analyzing the stocks in the context of a developing country such as Thailand (non-U.S. sample), stocks are ranked based on the size-sorted and return-sorted following methods proposed by Fama and French (2012, 2017). For every end-of-June of year y, portfolios are constructed by defining size breakpoints such that the big stocks represent market capitalization 90% of a country's market and small stocks cover the remaining 10 %. Big stocks and small stocks are defined as B and S, respectively.

Next, stocks are categorized based on their past 12 to 2 months' cumulative returns, with the top 70 and bottom 30 percentiles being designated as Winner (W), Neutral (N) representing 40% in the middle, and Loser (L). Next, monthly value-weighted portfolios are constructs as following procedure illustrated in Figure 5, are calculated their returns for the 2x3 portfolios (BW, BN, BL, SW, SN, SL) and are rebalanced end of June annually. Momentum strategy portfolios are then created by taking long positions in the winner portfolios and short positions in the loser portfolios, and their monthly returns are calculated accordingly, which this momentum strategy is referred to as the winner-minus-loser or WML portfolio. In this case, this study defines it as the standard momentum strategy.

$$MOM_t = \frac{(BW_t + SW_t)}{2} - \frac{(BL_t + SL_t)}{2} \qquad (2)$$

where BW_t Is the monthly return of big stocks portfolio and win the market at month t, SW_t is the monthly return of a small stocks portfolio and win the market at month t, BL_t is the monthly return of a big stocks portfolio and lose to the market at month t and SL_t is the monthly return of a small stock's portfolio and lose to the market at month t.

Figure 6 The procedure of portfolio construction using size-sorted and value-sorted criteria.
The figure above shows an example of how the standard momentum portfolio. The stocks are excluded if the share turnover is below the criteria of 0.01% annually. Then, stocks are sorted by their market capitalization, as big stocks cover 90% of the total market capitalization, and small stocks cover the remaining 10%. Next, the big and small stocks are sorted by their past cumulative return from month t-12 to month t-2, and portfolios are constructed as the top 30 percentile portfolio (defined as a winner) and the bottom 30 percentile (defined as a loser).



4.1.2 Enhanced momentum strategies

In investment strategy, volatility is a crucial factor in performance improvement through managing and timing the realized volatility to increase return. By decreasing the weight of the portfolio during high volatility periods and increasing it during low volatility, this mechanism enhances the momentum strategies and helps create consistent and sustainable profits without a loss in return.

There are four-momentum strategies from the literature that I aim to analyze in this study. First, this includes standard momentum or WML strategy defined as MOM. Then, I gather constant and dynamic volatility-scaled momentum approaches, which are constant volatility-scaled momentum, constant semi-volatility-scaled momentum, and dynamic-scaled momentum defined as cMOM, sMOM, and dMOM, respectively. As a way to determine the returns of each momentum strategy, it is necessary to calculate the appropriate scales or weights, which will be done as follows:

Constant volatility-scaled momentum (cMOM)

As proposed by Barroso and Santa-Clara (2015), This constant volatility-scaled momentum strategy focuses on managing risk by adjusting the standard volatility of the momentum portfolio to the constant target level and also applying forecast monthly volatility from their past returns. They believe that targeting the volatility level could be the key indicator in improvement in momentum investing. This target volatility is chosen so that the volatilities of the standard momentum and cMOM are identical, which makes the numerator side of the scaling constant throughout the study period. This approach can prevent selection bias because it solely relies on past information. Therefore, weight after scaling for this approach at month is calculated as follows:

$$w_{cMOM,t} = \frac{\sigma_{target}}{\hat{\sigma}_{cMOM,t}} \tag{3}$$

where σ_{target} is the constant target volatility level and $\hat{\sigma}_{cMOM,t}$ or $\mathbb{E}_{t-1}\left[\sigma_{cMOM,t}\right]$ is the forecasted monthly volatility.

Due to the time-varying property of forecasted volatility but this $\hat{\sigma}_{cMOM,t}$ can take values with infinite range (take values 0 if $\hat{\sigma}_{cMOM,t}$ is equal to infinity and is infinity for $\hat{\sigma}_{cMOM,t}$ has zero value), The monthly volatility forecast for month t is calculated from past daily returns of momentum in the previous six months (126 trading days).

$$\hat{\sigma}^2_{cMOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t}}{126} \tag{4}$$

where $R^2_{MOM,d-j,t}$ is the squared realized daily return on momentum portfolio over the last 126 days.

Finally, the monthly return of the constant volatility-scaled momentum strategy can be calculated by weighting with the inverse of the realized volatility in Equation (4)

$$R_{cMOM,t} = R_{MOM,t} \cdot w_{cMOM,t} \tag{5}$$

where $R_{MOM,t}$ is a monthly return of momentum strategy and $w_{cMOM,t}$ is scaling weight for the cMOM strategy.

Constant semi-volatility-scaled momentum (sMOM)

The constant semi-volatility-scaled momentum is constructed similarly to cMOM, but Wang and Yan (2021) substituted its full-sample volatility by semi- or downside volatility of momentum. Since they believe that this downside of the standard momentum can capture the performance of the volatility-managed momentum strategies. Then, downside volatility of each month can be calculated as follow by including indicator function that represents daily momentum returns affecting bear markets only, which this indicator has intention to capture only the downside of the standard momentum return or the negative returns from the standard approach:

$$\hat{\sigma}^2_{sMOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t} I_{|R_{MOM,d-j}<0|}}{126} \tag{6}$$

where $R^2_{MOM,d-j,t}$ is the squared realized daily return on momentum portfolio over the last 126 days, $I_{|R_{MOM,d-j}<0|}$ is equal to 1 if the j-lag market return is less than 0 and equal to zero otherwise.

Then, this study follows previously proposed research and constructs the volatility-managed portfolio by proportionally scaling the original portfolio by its inverse of lagged realized volatility:

$$f_{\sigma,t} = \frac{c^*}{\sigma_{t-1}} f_t \tag{7}$$

where $f_t = R_{MOM} - R_f$ is the monthly excess return for the original portfolio, c^* is a constant chosen such that f_t and $f_{\sigma,t}$ have the same full-sample volatility, f_t is the monthly excess return for the original portfolio and σ_{t-1} is the realized volatility of the original portfolio in month $t-1$.

Therefore, the scaling weight of the sMOM strategy is calculated as follows:

$$w_{sMOM} = \frac{c^*}{\hat{\sigma}_{sMOM,t}} \tag{8}$$

where $\hat{\sigma}_{sMOM,t}$ is semi- or downside volatility of momentum.

Then, the monthly return of semi-volatility-scaled momentum is computed by weighting the momentum return with the inverse if realized downside volatility and scaling with a static scalar relative to the overall full sample volatility,

$$R_{sMOM,t} = R_{MOM,t} \cdot w_{sMOM} \tag{9}$$

where $R_{MOM,t}$ is a monthly return of momentum strategy and $w_{sMOM,t}$ is scaling weight for the sMOM strategy.

Dynamic-scaled momentum (dMOM)

The dynamic-scaled momentum method was created by Daniel and Moskowitz (2016) and improves the previous constant volatility scaling method by also incorporating a forecast of momentum returns in the scaling process. The intuition behind this strategy is the anomalies in momentum investing that are defined as momentum crash which this strategies mainly constructed to mitigate this issue. Following prior literature, the dynamic scaling weight for momentum in month t in this study is defined in accordance with earlier research as follows:

$$w_{dMOM,t} = \left(\frac{1}{2\lambda}\right) \cdot \frac{\hat{\mu}_t}{\hat{\sigma}^2_{dMOM,t}} \tag{10}$$

where $\hat{\mu}_t = \mathbb{E}_{t-1}[\mu_t]$ is the predicted corresponding conditional anticipated return of momentum, $\hat{\sigma}^2_{dMOM,t} = \mathbb{E}_{t-1}\left[\sigma^2_{dMOM,t}\right]$ is the predicted corresponding conditional anticipated volatility of momentum, and lambda (λ) is a static constant adjusting the dynamic strategy to the entire sample volatility of momentum.

The time-series regression shown below is used to predict the anticipated return of momentum ($\hat{\mu}_t$) which this forecasted return are mainly estimated from the variance of the market excess return during the downturn of the market:

$$R^e_{MOM,t} = \gamma_0 + \gamma_{int} \cdot I_{Bear,t-1} \cdot \sigma^2_{RMRF,t-1} + \epsilon_t \tag{11}$$

where $I_{Bear,t-1}$ is a bearish indicator that equals one when the accumulated preceding 24 months' return of the market is less than zero (and zero otherwise), $\sigma^2_{RMRF,t-1}$ is the realized variance of $RMRF$ over the previous 126 trading days, and $RMRF$ is comprised of the value-weighted rate of returns of all available and legitimate securities less the rate of risk-free.

For forecasting the variance of the dynamic strategy, this study utilizes the same methodology as the constant-volatility scaling strategy.

$$\hat{\sigma}^2_{dMOM,t} = 21 \cdot \sum_{j=1}^{126} \frac{R^2_{MOM,d-j,t}}{126} \tag{12}$$

where $R^2_{MOM,d-j,t}$ is the squared realized daily return on momentum portfolio over the last 126 days, $I_{|R_{MOM,d-j}<0|}$ is equal to 1 if the j-lag market return is less than 0 and equal to zero otherwise.

Then, the monthly return dynamic-scaled momentum approach can be derived as follow:

$$R_{dMOM,t} = R_{MOM,t} \cdot w_{dMOM,t} \tag{13}$$

where $R_{MOM,t}$ is a monthly return of momentum strategy and $w_{dMOM,t}$ is scaling weight for the dMOM strategy.

4.2 Examine the possibility of applying momentum strategies in the Stock Exchange of Thailand

4.2.1 Compare the performance of different momentum strategies

The first objective of this study is to evaluate and compare the monthly performance of three enhanced momentum strategies (cMOM, sMOM, and dMOM) to the standard momentum strategy from many angles in the Stock

Exchange of Thailand. The comparison will be based on various metrics, including average returns, and the Sharpe ratio as practically understanding risk-adjusted return proposed by Sharpe (1998). Moreover, higher moment (i.e., skewness and kurtosis), as well as maximum drawdowns are also examined. The other aspects that might be important in measurement for further research are mentioned in the literature review section such as dynamic beta or dynamic risk associated in the investment strategies. Furthermore, the alternative measurement methods of each aspect are already stated which they might have their own advantages and disadvantages according to their application. As mention in the literature review section, there are various ways in comparison the momentum strategies together which this study focus on the conventional methods. These comparison practices are conducted referring to the previous literature proposed by Hanauer and Windmüller (2023) who showed the improvement in momentum strategies.

To interpret each result, according to the hypothesis that the volatility-scaled momentum strategies should outperform the standard one in terms of average returns. Additionally, the Sharpe ratio will provide insightful into the level of risk that is adjusted for the returns of the financial instruments. Skewness and kurtosis show the information about the distribution characteristic of each strategy, while Maximum drawdown is the maximum cumulative loss that can occur or is defined as the risk in investment.

To sum up, these results, except the return, will help to understand the riskiness inherent in each strategy. For instance, High returns with negative skewness (i.e., a slope on the left-hand side) and high kurtosis (i.e., a fat tail) may indicate a tendency towards large drawdowns. The formula of each output will be calculated as follow:

$$Average\ return\ (\%) = \frac{1}{t}\sum_{i=1}^{t} R_{i,t} \tag{14}$$

where $R_{i,t}$ is the monthly return of each strategy i in month t.

$$Sharpe\ ratio = \theta = \frac{\mathbb{E}[r_{p,i}] - r_f}{\sigma_{p,i}} \tag{15}$$

where $\mathbb{E}[r_{p,i}]$ is the expected return of the momentum portfolio i, r_f is the average risk-free rate as proxied by the average one-month Thai treasury bill and $\sigma_{p,i}$ is the volatility of the momentum portfolio i.

$$Skewness(R) = \mathbb{E}(R^3) = \frac{\mathbb{E}\left[\left(R_{i,t} - \mu_i\right)^3\right]}{\sigma_i^3} \tag{16}$$

$$Kurtosis(R) = \mathbb{E}(R^4) = \frac{\mathbb{E}\left[\left(R_{i,t} - \mu_i\right)^4\right]}{\sigma_i^4} \tag{17}$$

where $R_{i,t}$ is the monthly return of each strategy i in month t, μ_i is the average return of the momentum portfolio i and σ_i is the volatility of the momentum portfolio i.

Moreover, the maximum drawdown can be computed as the maximum cumulative loss between a peak and subsequent through in percentage (%).

4.2.2 Investigate performance-controlled transaction cost

The possibility of application of each momentum strategy, including MOM, cMOM, sMOM, and dMOM, can be evaluated through their transaction costs. This cost is the break-even cost or benchmark that every strategy must generate profits more than this level in order to be profitable in practical according to the hypothesis that momentum strategies should be profitable after taking into account transaction cost. The proxy for this transaction cost is what literature calls round-trip cost, proposed by Grundy and Martin (2015) and Barroso and Santa-Clara (2015). This round-trip cost tells the cost level in percentage that would reduce the momentum portfolio to be statistically insignificant in level. In this case, this study focuses on conventional significance levels that are 1% and 5%. For example, if the round-trip cost is 1%, it means that when transaction cost is at 1%, that strategy may not generate profits on average. This cost is mainly the ratio between the strategies average return and average weighted turnover, and it can be calculated at a certain α-significance level.[1]

$$Round - trip\ costs_{\alpha=5\%} = \left(1 - \frac{1.96}{t - stats_s}\right)\frac{\bar{\mu}_s}{\overline{TO}_s} \tag{18}$$

where $\bar{\mu}_s$ is the average monthly return for each strategy, $\overline{TO}_s$ is the average monthly turnover for each strategy and $t - stats_s$ is the t-statistic of return for each strategy.

In calculating the average monthly turnover, this study starts with calculating one-way portfolio monthly turnover for both long and short portfolio legs as the sum of the changes in weight of all stocks in the portfolio during each month.

$$Turnover_{t,Long(Short)} = 0.5 \times \sum_{i}^{N_t} \left| x_{i,t} - \tilde{x}_{i,t-1} \right| \tag{19}$$

where $x_{i,t}$ is the weight of stock i in the respective portfolio leg in month t, N_t amounts to the total number of stocks in the portfolio leg at month t, $r_{i,t}$ is the return of stock i during month t and $\tilde{x}_{i,t-1}$ is the weight at the end of month $t-1$ respectively at the beginning of month t, right before trading

This study defines the end-of-month $t-1$ weight ($\tilde{x}_{i,t-1}$) following the previous literature:

$$\tilde{x}_{i,t-1} = \frac{x_{i,t-1}(1 + r_{i,t-1})}{\sum_j^{N_t} x_{j,t-1}(1 + r_{j,t-1})} \tag{20}$$

Therefore, the turnover for a two-way portfolio with scaling is calculated by weighting the turnover in month t in accordance with the weight assigned in each momentum strategy weight as:

$$Turnover_{t,Long/Short} = 0.5 \times \sum_{i}^{N_t} \left| w_{scaled,t} x_{i,t} - w_{scaled,t-1} \tilde{x}_{i,t-1} \right| \tag{21}$$

where $w_{scaled,t}$ is the weight of the scaled momentum strategy

[1] This study chooses standard normal distribution value or Z-value from one-tailed distribution curve which is 2.58 for 1% significance level (instead of 1.96 for 5% significance level)

4.3 Study time-varying behavior of momentum portfolios

4.3.1 Time-varying beta

In order to assess the robustness of the momentum strategy for long sample periods in the Thai stock market, this study investigates the impact of market effects on these strategies, which can be examined from the sum of the market return coefficients. The time-varying behavior of the betas of the top and bottom deciles of the traditional momentum portfolio is analyzed with respect to market returns and lagged market returns. The beta difference between winner and loser portfolios shows the momentum crash period that occurs in the presence of sudden and significant market upswings, which can result in large negative returns in the traditional momentum portfolio. The betas tend to fluctuate substantially during these volatility periods, particularly for the first decile portfolio, where the beta tends to increase dramatically.

In this paper, the market betas of both winner and loser portfolios in traditional momentum strategies are analyzed using rolling regression with daily data. The market betas are estimated through regression analysis utilizing ten daily lags of the market return as follows and the sum of the estimated coefficients. $\hat{\beta}_0 + \hat{\beta}_1 + \cdots + \hat{\beta}_{10}$ will be shown as a line graph.

$$r_{i,t} = \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + \cdots + \beta_{10} r_{m,t-10} + \epsilon_t \tag{22}$$

where $r_{m,t}$, $r_{m,t-1}$, …, $r_{m,t-10}$ are one-day to ten-day lagged market returns, respectively

4.3.2 Comparison of performance of different momentum strategies during crisis

This study follows methodology 4.2.1 in comparing the performance of three enhanced momentum strategies which are constant volatility-scaled momentum, constant semi-volatility-scaled momentum, and dynamic momentum, against the standard momentum strategy in risk and return metrics as COVID-19 is the pandemic that made market panic causing the Thai stock market to plummet with high volatility during early 2019 to late 2020. The analysis mainly focuses on the sub-period surrounding the COVID-19 period, which covers from June 2018 until December 2022. This period will be divided into three sub-periods, which are before COVID-19, during COVID-19 (as defined by momentum crashes period form time-varying beta), and after COVID-19 (after crashes period). The results are anticipated to support the hypothesis that the enhanced momentum strategies should outperform the standard approach even during crisis periods.

4.3.3 Asymmetry of the momentum performance in bull and bear markets

To study the time-varying behavior of four-momentum strategies, including traditional winner-minus-loser momentum, cMOM, sMOM, and dMOM, on a monthly basis. This study evaluates whether the coefficients have significant asymmetry or not depending on economic and statistical significance. The robustness of the strategy is analyzed based on its performance in both bullish and bearish market conditions. The alphas and betas are interpreted according to the hypothesis that these strategies will exhibit consistent performance across varying market conditions. Equations (23) and (24) below try to capture both abnormal returns and market-beta differences in bear and bull markets, in bull market conditions, $I_{Bear,t-1}$ is substituted with $I_{Bull,t-1}$ which is an indicator function identifying bull markets. The rationale behind the market condition dummy variable ($I_{Bear,t-1}$) is aims to differentiate the beta of the momentum portfolio during bear and normal market conditions. Also, the ways of defining the dummy variable might act differently according to the literature that each study refer to. This indicator could be binary variable as identified by this study and the previous literature by Daniel and Moskowitz (2016), or could be alternatively modeled as suggested by Kim (1994), Caner and Hansen (2004), and Gonzalez et al. (2017) which are already mentioned in the literature review section. Moreover, the contemporaneous up-market indicator ($I_{Up,t}$) is utilized to differentiate the impact of beta when the contemporaneous market return is positive ($R^e_{m,t} > 0$ and $I_{Up,t} = 1$) versus when it is not ($R^e_{m,t} \leq 0$ and $I_{Up,t} = 0$).

This study focuses on all alphas and betas in these two equations in order to summarize the asymmetry characteristics. In both markets, α_0 and α_{Bear} are anticipated to be positive and significance because good investment options should generate abnormal returns in general. However, the results of betas are interpreted differently due to market conditions. During bear markets, β_0 are expected to be positive, while β_{Bear} are expected to be negative, indicating that the momentum portfolio behaves like a trend following investment. Furthermore, $\beta_{Bear,Up}$ are expected to be positive as it follows the contemporaneous market return. In contrast to the bear market, β_0 are expected to be negative, while β_{Bear} are expected to be positive in bull markets. Additionally, if $\beta_{Bull,Down}$ shows negative value, it means this portfolio's sensitivity is lower when the market trend reverses during the bull run. In conclusion, performance characteristics in both bull and bear markets are analyzed to make sure that the results address the main issues of this study that holding the momentum makes positive profit through the period as negative correlation with the bear market conditions, while positive correlation with the bull market conditions.

$$R^e_{i,t} = \left[\alpha_0 + \alpha_{Bear} I_{Bear,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ +I_{Bear,t-1} I_{Up,t} \beta_{Bear,Up} \end{bmatrix} R^e_{m,t} + \epsilon_t \tag{23}$$

$$R^e_{i,t} = \left[\alpha_0 + \alpha_{Bull} I_{Bull,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ +I_{Bull,t-1} I_{Down,t} \beta_{Bull,Down} \end{bmatrix} R^e_{m,t} + \epsilon_t \tag{24}$$

where α_0 is abnormal return during normal conditions, α_{Bear} is the additional abnormal return affected differences in bear markets, α_{Bull} is the additional abnormal return affected differences in bull markets, β_0 is market beta or sensitivity, β_{Bear} is the sensitivity of the momentum portfolios during bearish markets, β_{Bull} is addition sensitivity of the momentum portfolios during bullish markets, $\beta_{Bear,Up}$ is the addition sensitivity of momentum portfolios during market rebound in bearish markets, $\beta_{Bull,Down}$ is the additional sensitivity of momentum portfolios during market reversal in bullish markets, $I_{Bear,t-1}$ is downtrend market indicator that has the value of one when the accumulated SET index yield in the preceding 24 months is lower than zero and zero otherwise, $I_{Up,t}$ is a contemporaneous market reversal indicator variable which shows value of one on condition that the excess SET index yield is greater than the rate of risk-free in month t ($R^e_{m,t} > 0$), $I_{Bull,t-1}$ is an uptrend market indicator which is one when the accumulated SET index yield in the previous 24 months is greater than zero or defined as $1 - I_{Bear,t-1}$, and zero otherwise, $I_{Down,t}$ is a contemporaneous market rebound indicator variable that value of one will be shown when the excess SET index output is less than the rate of risk-free at that month t ($R^e_{m,t} < 0$) and $R^e_{m,t}$ is the excess return for the market value-weighted index in month t above the zero-risk rate.

CHAPTER 5
Empirical Result

5.1 The analysis of the performance of volatility-managed portfolios

Section 5.1 provides a comprehensive analysis of enhanced momentum strategies, including cMOM, sMOM, and dMOM, as compared to the standard momentum (MOM) approach used as the benchmark. The analysis evaluates the returns and other characteristics of these momentum strategies in the Thai stock market from January 2013 to December 2022. Figure 7 illustrates line charts representing the cumulative portfolio value of a 1 Baht investment in each strategy, starting from January 2013 as month 1. These charts visually depict the performance of each momentum strategy over the analyzed period. Also, table 4 presents the summary statistics of each momentum portfolio's return. These statistics provide a concise overview of the performance and characteristics of each momentum strategy, allowing for a quantitative assessment of their effectiveness in generating returns. Overall, this section offers a rigorous analysis of enhanced momentum strategies in the Thai stock market, providing valuable insights into their performance and potential advantages over the standard momentum approach.

From Table 4, overall, the analysis reveals that all enhanced momentum strategies outperform the standard momentum approach in terms of both value and positive returns. The standard approach yielded an average annual return of -0.94%, with the standard deviation of 3.56% in the standard momentum, cMOM incorporates this volatility as its targeted volatility. While, c* is chosen at 0.0256 in order to make sMOM excess volatility equal to MOM excess volatility and λ is chosen at 0.0219 to make dMOM volatility equal to MOM volatility. While the cMOM, sMOM, and dMOM strategies delivered returns of 2.26%, 5.67%, and 1.74% per year, respectively. While these returns are not statistically significant, all the enhanced strategies generate economically positive excess returns compared with MOM, which is statistically significant at 3.20% (t-statistic is 1.87), 6.60% (t-statistic is 2.44), and 2.67% (t-statistic is 1.85) for cMOM, sMOM, and dMOM, respectively. The Sharpe ratio for all enhanced approaches also increases from negative to positive. These results are consistent with Hanauer and Windmüller (2023), which found that all three enhanced momentum strategies increase the Sharpe ratio, and support the hypothesis that volatility-scaled momentum strategies generate returns above the standard momentum approach. However, these positive excess returns come with higher standard deviations than the standard approach, but not much for cMOM and dMOM, while sMOM shows the highest volatility as it also shows the highest excess return. These results for sMOM are consistent with Wang and Yan (2021), as this approach takes into account downside volatility in its weight by adjusting the forecasted volatility with an indicator that is equal to one if the momentum return on that day is negative and vice versa. When the past six-month volatility is low, sMOM tends to increase the weight on that month, as it is an indicator that the past performance of MOM has been strong, and vice versa. Since MOM returns are mostly positive, this strategy adds weight at the right time, making it profitable even when MOM does not perform well.

All enhanced strategies have lower skewness and kurtosis, especially sMOM, which shows not only lower magnitudes but also a positive sign for skewness, indicating that the returns distribution slope is on the right-hand side. These characteristics of the returns indicate a lower maximum drawdown compared to MOM. The maximum drawdown for all strategies occurred after the COVID-19 pandemic affected the Stock Exchange of Thailand until the end of the sample period. During the entirety of the analyzed period, it is important to note that all three enhanced momentum strategies may not exhibit exceptional performance when compared to the standard momentum approach. This observation can be attributed to the influence of the COVID-19 pandemic, which had an impact on market conditions. Nevertheless, these findings align with the research conducted by Hanauer and Windmüller (2023), which indicates that these volatility-managed portfolios have the potential to mitigate crash risks as this study shows lower maximum drawdown.

Figure 7 Cumulative performance of all four-momentum strategies in the overall period.
This figure shows the cumulative performance of 1 Baht investment for each momentum strategy, i.e., MOM, cMOM, sMOM, and dMOM. This figure covers the overall sample period ranges from January 2013 to December 2022

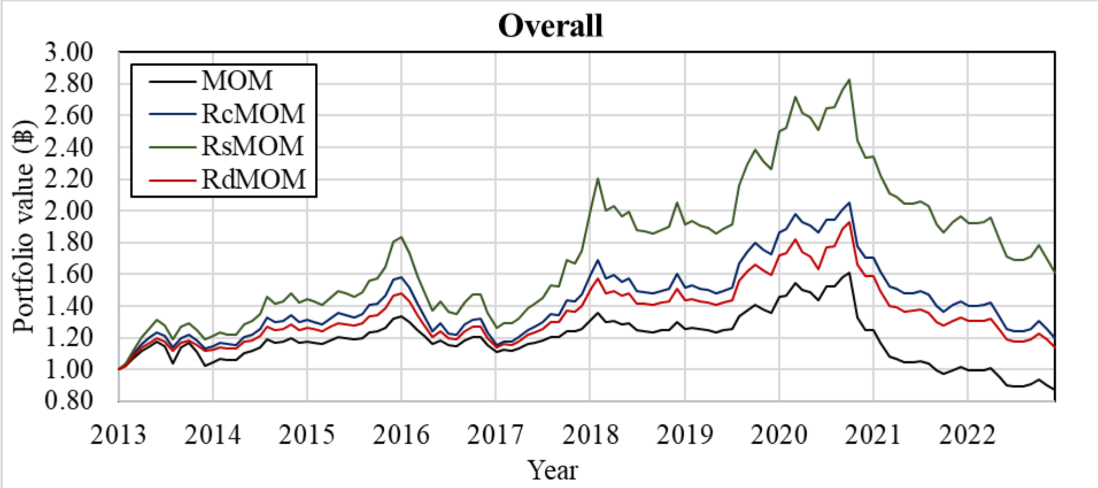


Table 4 Summary statistics for all four-momentum strategies in the overall period.
This table shows the statistics information covering the full-sample period spans throughout January 2013 until December 2022 for all standard and enhanced momentum techniques that are MOM, cMOM, sMOM, and dMOM: (1) Average monthly return (in %), (2) Return t-statistics, (3) Standard deviation, (4) Excess MOM return, (5) Excess return t-statistics, (6) Standard deviation, (7) the Sharpe ratio, (8) Skewness, (9) Kurtosis, and (10) Maximum drawdown (in %) as it shows the largest drawdown which can occur during investment. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *. The value of average returns' t-statistics is shown in parentheses.

	MOM	cMOM	sMOM	dMOM
Average return	-0.08%	0.19%	0.47%	0.14%
	(-0.31)	(0.68)	(1.39)	(0.57)
Standard deviation	3.56%	3.89%	4.82%	3.60%
Excess MOM return		0.27%*	0.55%**	0.22%*
		(1.87)	(2.44)	(1.85)
Standard deviation		1.43%	2.26%	1.20%
Sharpe ratio	-0.06	0.02	0.07	0.01
Skewness	-1.12	-0.27	0.17	-0.35
Kurtosis	4.81	0.57	0.54	1.19
Maximum Drawdown	46.03%	41.78%	43.02%	40.90%

5.2 Identify momentum crashes

In this section 5.2, this study examines the conditions of the traditional momentum portfolio and investigates whether momentum crashes occur or not. The focus is on the momentum crash period surrounding the COVID-19 pandemic. To analyze this, regression analysis is employed using regression equation 22, as detailed in the methodology section. The regression analysis covers the period from January 2018 to December 2022. This study conducts 126-day rolling regressions of the winner decile portfolio, using the past 10-day lagged market returns as the independent variable. By summing the beta coefficients, the overall effect of market factors on the winner portfolio is evaluated. Additionally, the same regression analysis is performed for the loser portfolio.

Figure 8 displays the combined impact of market factors, represented by the sum of the betas, on both the winner portfolio (solid line) and the loser portfolio (dashed line). This visualization showcases the alternating dynamics and crossovers between the two portfolios. The beta coefficients of both winners and losers in traditional momentum strategies display significant variations, particularly during periods of crisis. Specifically, during such periods, the betas of loser portfolios increase substantially, leading to high fluctuation and outperforming the betas of the winner portfolio.

As depicted in Figure 8 below, the overlapping sample period occurred between April 2020 and April 2021, indicating that the COVID-19 pandemic resulted in momentum crashes during this period. The time-varying beta analysis highlights the betas before, during, and after the momentum crashes. This finding aligns with the observations made by Daniel and Moskowitz (2016), as it demonstrates that the loser portfolio was more significantly influenced by market returns during this crash period. Notably, this momentum crash persisted for several months, and our study confirms its occurrence in the Stock Exchange of Thailand.

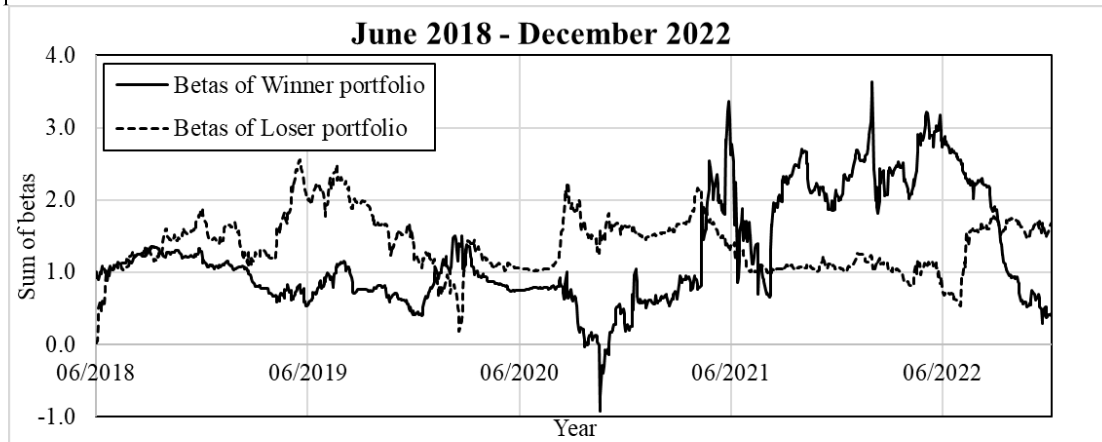
Figure 8 The winner and loser of traditional momentum portfolio's betas.
This figure demonstrates the market betas from June 2018 to December 2022. The betas are estimated by conducting a set of 6 months (126 trading days) rolling regression of the momentum portfolio excess returns on the contemporaneous excess market return which the regression is as follows:

$$r_{i,t} = \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + \cdots + \beta_{10} r_{m,t-10} + \epsilon_t$$

Next, ten daily lags beta of the market return are summed together as follows:

$$\hat{\beta}_0 + \hat{\beta}_1 + \cdots + \hat{\beta}_{10}$$

Then, this study plots the first decile (winner) and the last decile (loser) of the traditional momentum portfolio.



As there are no explicit criteria for dividing the COVID-19 pandemic period in Thailand into pre- and post-COVID-19 pandemic. By addressing this issue, Figure 9 below illustrates how further analysis is conducted by utilizing the momentum crashes period from Figure 8 above as a criterion for dividing the full-sample period. As momentum crashes refer to the period of anomalies in momentum investing, it arises when the market undergoes a substantial rebound after a period of downturn. Therefore, the occurrence of momentum crashes serves as a great signal indicating that the market has reached a trough and is beginning its recovery. These results are used to delineate the sample period, enabling a more focused investigation of the subsequent market dynamics.

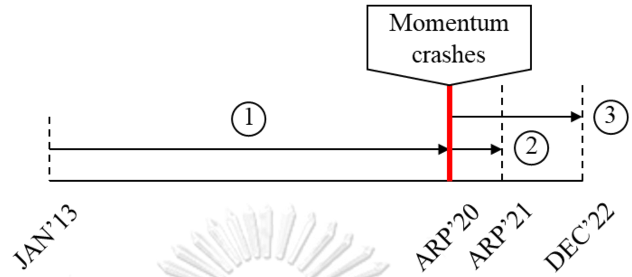
Then, the full-sample period ranging from January 2013 to December 2022 is classified into three subperiods as follows:

- Before the COVID-19 pandemic: January 2013 to March 2020, as divided by the momentum crashes.
- One year after the COVID-19 pandemic: one year after the momentum crashes, which ranges from April 2020 to April 2021.

- Two years after the COVID-19 pandemic: two years after the momentum crashes, which ranges from April 2020 to December 2022.

Figure 9 The demonstration of 3 subperiods for this study.

The figure above shows the timeline of the sample period of this study, which is divided into three subperiods by the momentum crashes from the time-varying betas that are (1) From January 2013 to April 2020, (2) From April 2020 to April 2021, and (3) From April 2020 to December 2022



5.3 Subsample analysis

Section 5.3 presents the subsample analysis, which aligns with the time period discussed in section 5.2 and conducts a comprehensive performance analysis accordingly. This section's main goal is to assess the effectiveness of each momentum strategy inside each subperiod in comparison to how well they performed over the whole dataset. Additionally, it intends to compare the performance of three improved momentum techniques to the traditional momentum strategy during this particular subperiod.

Starting with the subsample period, which ranges from January 2013 to March 2020 (defined as before the COVID-19 pandemic). Figure 10 below shows a line chart of as cumulative return of 1 Baht investment in each strategy, starting from January 2013 as month one, and Table 5 presents the summary statistics of each momentum portfolio's return. Similar to the overall period before the COVID-19 pandemic, all three enhanced momentum strategies outperformed the standard momentum strategies, with all momentum portfolios showing positive returns higher than the market's 1.31% annually. MOM yielded an average return of 6.16% per annum and the standard deviation of 3.09% which relatively low compare with the full-sample period, and this volatility is chosen as σ_{target} for cMOM, while c* and λ are valued at 0.0284 and 0.0229 are chosen for sMOM and dMOM, respectively, in order to adjusting their weight referring previous literature. While cMOM, sMOM, and dMOM generated returns of 9.71%, 14.62%, and 8.42%, respectively. In contrast to the overall period, the returns during this period were statistically significant at 1% for all three enhanced momentum approaches and 5% for the standard MOM. The annual excess returns from MOM were positive and statistically significant at 3.56%, 8.47%, and 2.27% for cMOM, sMOM, and dMOM, respectively.

In conclusion, based on this sub-sample analysis, all momentum strategies exhibit comparable rankings and orders when compared to the full sample. Additionally, the three enhanced momentum strategies consistently outperform the standard approach. Furthermore, it is noteworthy that all momentum strategies in this sub-sample generate positive outcome at the 1 percent significant level. In contrast, only the improved momentum techniques show positive returns in the full-sample analysis, although these are not statistically significant.

Similar to the overall period, all enhanced strategies showed an improvement in the Sharpe ratio, with a minimum of 50%, consistent with Hanauer and Windmüller (2023) and the hypothesis that volatility-scaled momentum strategies generate returns above the standard momentum approach. Furthermore, they also came with higher volatility, with sMOM showing the highest value, as well as its returns. The sMOM outperformed the others during normal conditions, consistent with Wang and Yan (2021), as it incorporated downside volatility in its weight. During this time, as most of the MOM returns were positive, sMOM's forecasted volatility was low, causing this strategy to put on more weight and generate even higher returns.

The largest drawdown for the strategies occurred from 2015 to 2017. In 2015, the Thai stock market was affected by a slowdown in the Chinese economy, which decreased demand for Thai exports, causing the country's GDP growth to slow down. Political instability in Thailand also impacted the stock market, with the military government taking control of the country in May 2014, leading to a period of political uncertainty and instability. However, from 2016 to 2017, the Thai stock market rebounded, with the SET index reaching an all-time high. The strong performance was due to the government's infrastructure investment plans and a recovery in commodity prices, which boosted the country's exports and GDP growth. The largest drawdowns for the sMOM, cMOM, and dMOM strategies were 30.93%, 27.09%, and 23.02%, respectively. sMOM had the largest drawdown due to its significant outperformance of the market before 2015, making its decline look more pronounced. Nevertheless, it remained the most outperforming momentum portfolio during this period.

Lastly, higher moment of return including skewness and kurtosis from the enhanced and standard MOM approach were analyzed. Our findings indicate that the dispersion of the enhanced portfolios' returns was more normally distributed than that of the standard MOM approach. While cMOM and dMOM had the same negative skewness as the standard MOM, they exhibited lower magnitudes of both skewness and kurtosis. In contrast, sMOM exhibited better results, with not only a lower magnitude but also a positive skewness, indicating that its distribution was more likely to be normal than that of the standard MOM approach.

Figure 10 Cumulative performance of all four-momentum strategies before COVID-19.
This figure shows the cumulative performance of 1 Baht investment for each momentum strategy, i.e., MOM, cMOM, sMOM, and dMOM. This figure covers the period before the COVID-19 pandemic, which ranges from January 2013 to May 2020

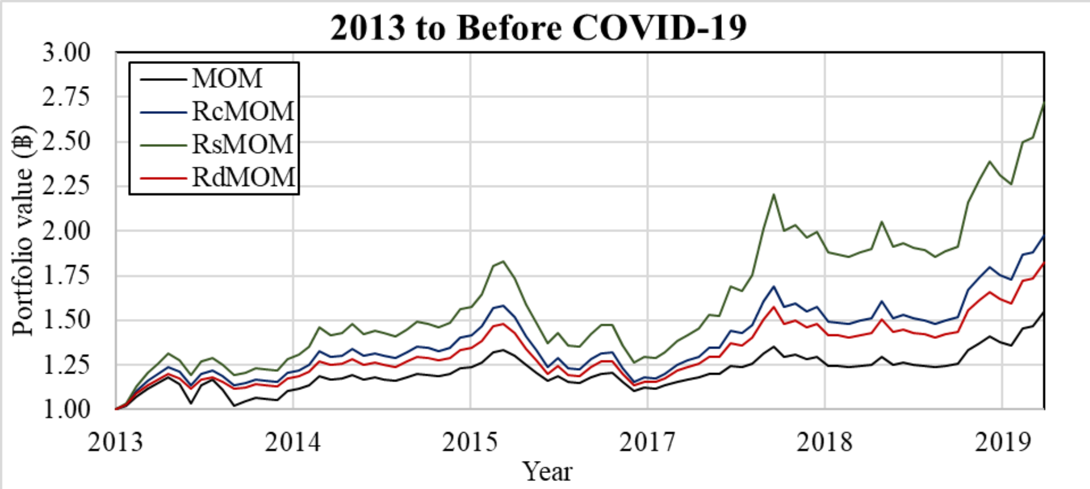


Table 5 Summary statistics for all four momentum strategies before COVID-19.
This table shows the statistics information covering the period before the momentum crash spans throughout January 2013 until May 2020 for all standard and enhanced momentum techniques that are MOM, cMOM, sMOM, and dMOM: (1) Average monthly return (in %), (2) Return t-statistics, (3) Standard deviation, (4) Excess MOM return, (5) Excess return t-statistics, (6) Standard deviation, (7) the Sharpe ratio, (8) Skewness, (9) Kurtosis, and (10) Maximum drawdown (in %) as it shows the largest drawdown which can occur during investment. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *. The value of average returns' t-statistics is shown in parentheses.

	MOM	cMOM	sMOM	dMOM
Average return	0.51%**	0.81%***	1.22%***	0.70%***
	(2.48)	(3.15)	(3.67)	(3.20)
Standard deviation	3.09%	3.83%	4.95%	3.27%
Excess MOM return		0.30%***	0.71%***	0.19%**
		(2.69)	(3.91)	(2.12)
Standard deviation		1.56%	2.55%	1.26%
Sharpe ratio	0.13	0.18	0.22	0.18
Skewness	-0.27	-0.11	0.19	-0.08
Kurtosis	1.43	0.22	0.13	0.22
Maximum Drawdown	17.00%	27.09%	30.93%	23.02%

This study delves deeper into the analysis of a subsample period ranging from April 2020 to April 2021, representing one year after the onset of the COVID-19 pandemic. Figure 11, presented below, illustrates a line chart depicting the cumulative return of a 1 Baht investment for each strategy, starting from April 2020 (designated as month 1). Additionally, Table 6 provides a comprehensive overview of the summary statistics pertaining to the returns of each momentum portfolio. During one year after-COVID-19 pandemic sub-period of momentum crashes defined by time-varying betas, an analysis was conducted on the performance of all four momentum strategies from April 2020 to April 2021. MOM, cMOM, and sMOM tended to move together, which was opposite to dMOM.

According to the weight adjustment, this target volatility is chosen at 6.04% which relatively high relative to the period before the momentum crash, while value of c* at 0.0342 and λ at 1.1265 are chosen for sMOM and dMOM, respectively, which these static constants are relatively high as the effect of the COVID-19 pandemic. These chosen constants make their enhanced strategies have adjusted volatility complied with the previous literature. The study began with the standard momentum (MOM), constant volatility-scaled (cMOM), and constant semi-volatility-scaled (sMOM) approaches, which demonstrated negative annual returns of -32.04%, -42.00%, and -27.44%, respectively. These three returns were statistically significant at 1%. In contrast, dMOM showed a positive return of 56.31% per annum, which was statistically significant at 5%. Specifically, the excess return for dMOM was as high as 56.31% annually. The result for cMOM is not consistent with the hypothesis that enhanced momentum strategies should demonstrate better performance but consistent with Hanauer and Windmüller (2023) that all enhanced approaches outperform and increase the Sharpe ratio, and the hypothesis that the volatility-scaled momentum strategies will generate returns above the standard momentum approach, and also Barroso and Santa-Clara (2015) as portfolios that were constructed during this period would face high volatility of the momentum return. As cMOM fixed the volatility to be similar to MOM, which was really high during this crash period, it made its weight even more, leading to worse returns than its standard portfolio, but not statistically significant. Additionally, sMOM took into account more than half of its returns to calculate its forecasted volatility, causing high volatility and reducing its weight during this crisis period. Subsequently, the returns were better than MOM, which was consistent with Wang and Yan (2021) but still moved together. The dynamic-scaled momentum strategy, constructed by Daniel and Moskowitz (2016) to tackle the momentum crash, performed really well in the Stock Exchange of Thailand as well. As it expects its return to be a negative value, this strategy makes it weigh negative or short sell against its portfolio.

When comparing the results to the full-sample analysis, it is observed that only the dMOM (dynamic-scaled momentum strategy) outperforms the MOM, which aligns with the findings from the full-sample analysis. Conversely, the remaining strategies exhibit performance similar to that of the full sample. Notably, during this subsample period characterized by the momentum crash, the study identifies a higher standard deviation, nearly double that of the full sample, with volatility ranging from 6-8%. This increase in volatility can be attributed to the impact of the COVID-19 pandemic, which significantly affected the Thai stock market. The elevated volatility in the returns of the momentum strategies can be reasonably attributed to this unprecedented market situation.

Although all enhanced momentum strategies had less magnitude for kurtosis and skewness, there was an exception for the cMOM approach, which exhibited the largest drawdown at -43.71%, which was larger than the standard momentum approach (maximum drawdown of -34.08%). The sMOM and dMOM had maximum drawdowns of 30.98% and 16.76%, respectively.

Figure 11 Cumulative performance of all four-momentum strategies one year after COVID-19. This figure shows the cumulative performance of 1 Baht investment for each momentum strategy, i.e., MOM, cMOM, sMOM, and dMOM. This figure covers the period one year after-COVID-19 pandemic, which ranges from April 2020 to April 2021

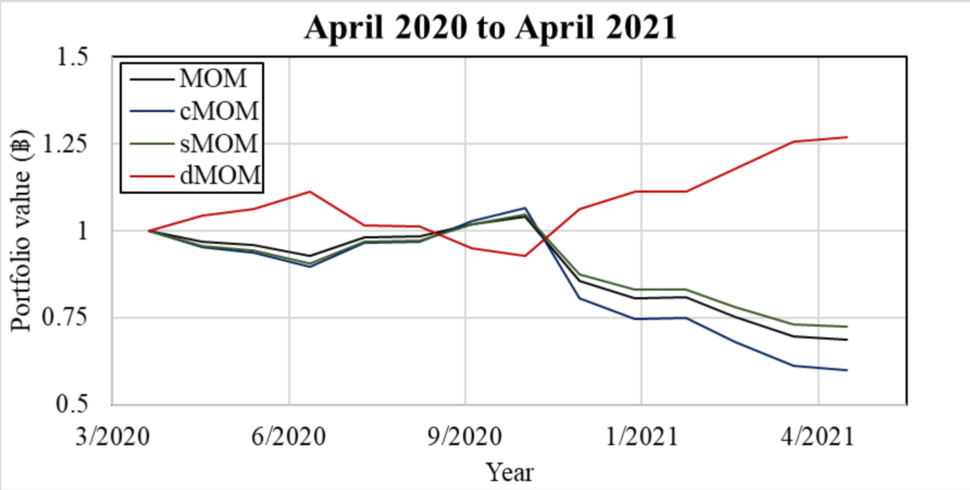


Table 6 Summary statistics for all four-momentum strategies one year after COVID-19. This table shows the statistics information covering one year after the momentum crash spans throughout April 2020 until April 2021 for all standard and enhanced momentum techniques that are MOM, cMOM, sMOM, and dMOM: (1) Average monthly return (in %), (2) Return t-statistics, (3) Standard deviation, (4) Excess MOM return, (5) Excess return t-statistics, (6) Standard deviation, (7) the Sharpe ratio, (8) Skewness, (9) Kurtosis, and (10) Maximum drawdown (in %) as it shows the largest drawdown which can occur during investment. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *. The value of average returns' t-statistics is shown in parentheses.

	MOM	cMOM	sMOM	dMOM
Average return	-2.67%***	-3.50%***	-2.29%***	2.02%**
	(-3.13)	(-2.97)	(-2.72)	(2.37)
Standard deviation	6.04%	8.33%	5.94%	6.04%
Excess MOM return		-0.83%	0.38%**	4.69%*
		(-1.61)	(2.18)	(1.75)
Standard deviation		2.31%	0.78%	11.99%
Sharpe ratio	-0.46	-0.43	-0.40	0.32
Skewness	-1.20	-1.14	-0.81	0.18
Kurtosis	2.49	2.33	1.82	0.85
Maximum Drawdown	34.08%	43.71%	30.98%	16.76%

Additionally, this study undertakes an analysis of a subsample period spanning from April 2020 to December 2021, encompassing two years after the occurrence of the COVID-19 pandemic. The line chart in Figure 12, provided below, illustrates the cumulative return of a 1 Baht investment for each strategy, commencing from April 2013 as month 1. Furthermore, Table 7 presents a comprehensive summary of the statistical measures pertaining to the returns of each momentum portfolio during this period. During the 2-year after-COVID-19 pandemic sub-period, the volatility of cMOM is targeted at 4.26%, sMOM choose c* value of 0.0329, and dMOM chose λ value of 0.3133, which these constants are lower than the period one year after the pandemic as the momentum strategy still got affected by the anomalies in its strategies. The performance of the MOM, cMOM, and sMOM momentum strategies was mostly parallel with negative returns of -19.64%, -22.01%, and -20.77%, respectively, all statistically significant at the 1% level. However, their excess returns did not demonstrate statistical significance, suggesting that most of the time, these three approaches yielded similar returns. In contrast, dMOM showed positive and statistically significant average and excess returns of 17.77% annually (t-statistic is 2.46) and 37.41% yearly (t-statistic is 2.60), respectively.

These results are similar to the 1-year after-COVID-19 pandemic sub-period, with the exception that the positions of sMOM and cMOM are swapped, as cMOM shows the lowest return without statistical significance relative to MOM, and sMOM generates a return lower than MOM without statistical significance, but still outperforms cMOM, consistent with Wang and Yan (2021). These results are not consistent with the hypothesis that volatility-scaled momentum strategies will generate returns above the standard momentum approach and Hanauer and Windmüller (2023), as cMOM's fixed volatility to be similar to MOM, whose volatility remains high after the crash period, making its weight even more significant, after adding up the weight to MOM, it generates return similarly to its standard portfolio. Additionally, sMOM's weight reduces during this crisis period due to its calculation of forecasted volatility as it takes into account more than half of its returns, causing high volatility; subsequently, the return is also similar to MOM. The momentum crash was effectively addressed by Daniel and Moskowitz (2016) through the dynamic-scaled momentum strategy, which also demonstrated excellent performance in the Stock Exchange of Thailand. This strategy anticipates negative returns and thus adjusts its portfolio weights to include negative values or engage in short selling.

When comparing the results to the full-sample analysis, it is observed that only the dMOM (dynamic momentum) strategy outperforms the MOM (momentum) strategy, consistent with both the full-sample analysis and the previous subsample analysis (one year after the COVID-19 pandemic). Conversely, the other strategies demonstrate performance that is not in line with the full-sample analysis but exhibits a similar direction. During this subsample period, which encompasses a period affected by the momentum crash, the study reveals a higher standard deviation compared to the full sample, which typically shows a range of 3-5%. However, in this subsample, there is a slight increment of 1% in volatility, with values ranging from 4-5%. It is reasonable to attribute this increase in volatility in the momentum strategies' returns to the impact of the COVID-19 pandemic. However, the effect is not as pronounced as in the previous subsample (one year after the COVID-19 pandemic) since the latter was directly hit by the pandemic.

Although all enhanced momentum strategies had less magnitude for kurtosis and skewness, there was an exception for the cMOM and sMOM approaches, which exhibited the largest drawdown at -50.02% and 48.13%, respectively, which was larger than the standard momentum approach (maximum drawdown of -46.03%). In contrast, dMOM had low maximum drawdowns of 15.90%, as it almost moved upward throughout this subperiod.

Figure 12 Cumulative performance of all four-momentum strategies two years after COVID-19. This figure shows the cumulative performance of 1 Baht investment for each momentum strategy, i.e., MOM, cMOM, sMOM, and dMOM. This figure covers the period two years after-COVID-19 pandemic, which ranges from April 2020 to December 2022

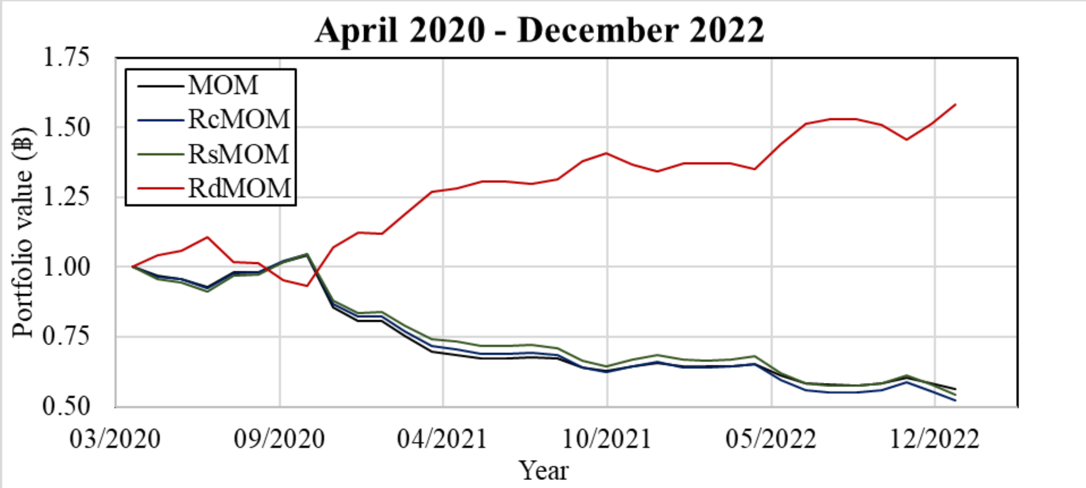


Table 7 Summary statistics for all four-momentum strategies two years after COVID-19. This table shows the statistics information covering two years after the momentum crash spans throughout April 2020 until December 2022 for all standard and enhanced momentum techniques that are MOM, cMOM, sMOM, and dMOM: (1) Average monthly return (in %), (2) Return t-statistics, (3) Standard deviation, (4) Excess MOM return, (5) Excess return t-statistics, (6) Standard deviation, (7) the Sharpe ratio, (8) Skewness, (9) Kurtosis, and (10) Maximum drawdown (in %) as it shows the largest drawdown which can occur during investment. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *. The value of average returns' t-statistics is shown in parentheses.

	MOM	cMOM	sMOM	dMOM
Average return	-1.64%***	-1.83%***	-1.73%***	1.48%**
	(-2.72)	(-2.83)	(-2.71)	(2.46)
Standard deviation	4.26%	4.59%	4.52%	4.26%
Excess MOM return		-0.20%	-0.09%	3.12%***
		(-1.47)	(-0.58)	(2.60)
Standard deviation		0.95%	1.14%	8.47%
Sharpe ratio	-0.39	-0.40	-0.38	0.35
Skewness	-1.68	-1.07	-0.78	0.62
Kurtosis	5.59	2.46	1.66	2.43
Maximum Drawdown	46.03%	50.02%	48.13%	15.90%

5.4 Investigate performance-controlled transaction cost

Section 5.4 provides a comprehensive analysis of the performance after including the transaction cost in order to evaluate if it is still profitable or not. The examination focuses on a period characterized by normal market conditions, spanning from January 2013 to March 2020, which are defined as before the COVID-19 pandemic. In Table 8, provided below, detailed information is presented regarding the turnover and the associated round-trip costs, considering significance levels of 1% and 5% for all momentum strategies. By having taken contracts in winners and selling contracts in losers, momentum investment strategies are often built with no upfront costs. However, transaction fees, which are frequently ignored in earlier studies, might significantly affect the returns of such tactics. This study presents the returns of momentum investment strategies in Table 5 without including transaction costs. Table 8 also displays the average monthly turnover of a strategy-weighted long-short portfolio, with a value of 9.24% for the standard momentum approach (MOM). The turnover increases for enhanced momentum strategies due to the time-varying weight. Specifically, the turnover is 12.83% for cMOM, 13.82% for dMOM, and 17.06% for sMOM, the highest among all the strategies. It should be noted that the relatively low turnover in the Thai stock market is due to the limited number of stocks, which makes round-trip costs more feasible.

The round-trip costs are the percentages of transaction costs that, at confidence intervals of 5% and 1%, would make the profits from the methods statistically insignificant. Table 9 demonstrates that when transaction costs are less than 1.16 percent, the traditional momentum strategy is only 5% certain that it will not provide profits. In contrast, the round-trip costs for enhanced momentum strategies are higher than those for the standard MOM, with values of 2.38% for cMOM, 1.97% for dMOM, and 3.33% for sMOM.

$$Round - trip\ costs_{\alpha=1\%} = \left(1 - \frac{2.58}{t - stats_s}\right)\frac{\bar{\mu}_s}{\overline{TO}_s} \tag{25}$$

Furthermore, increasing the significance level to 1% renders the standard momentum approach impossible for investment, as the z-value changes from 1.96 to 2.58 in the round-trip cost formula. In contrast, all enhanced momentum strategies remain viable, as cMOM requires transaction costs of less than 1.14% to achieve a 1% confidence level of generating profits. Similarly, sMOM requires a transaction cost of 1.14%, and dMOM needs 0.98% to achieve the same level of confidence. This indicates that enhanced momentum strategies have greater robustness against transaction costs than the standard momentum approach.

In conclusion, our analysis highlights the importance of considering transaction costs when evaluating the performance of momentum investment strategies. Although the round-trip costs for enhanced momentum strategies are higher than those for the standard momentum approach, they remain profitable at higher significance levels which is consistent with Hanauer and Windmüller (2023) and the hypothesis that after taking into account transaction cost, the enhanced portfolio should generate profit. Therefore, investors should carefully consider transaction costs and their investment objectives when selecting a momentum investment strategy.

Table 8 Turnover and round-trip costs.
This table shows the turnover and round-trip cost computed for MOM, cMOM, sMOM, and dMOM: (1) Average monthly turnover (in %), (2) Round-trip cost at 5% significance level, and (3) Round-trip cost at 1% significance level. The sample period is based on the period before the COVID-19 pandemic, which is from January 2013 to March 2020

	MOM	**cMOM**	**sMOM**	**dMOM**
Turnover	9.24%	12.83%	17.06%	13.82%
Round-trip cost at 5% significance level	1.16%	2.38%	3.33%	1.97%
Round-trip cost at 1% significance level	-0.23%	1.14%	2.12%	0.98%

5.5 Asymmetry of the momentum performance in bull and bear markets

Section 5.5 offers a comprehensive overview of the characteristic differences between the returns of each momentum strategy and the market return, specifically during bull and bear market conditions. The examination is conducted for both the full-sample dataset and three subsamples, following similar periods to the performance analysis of the portfolios. It aims to compare the characteristics of all momentum strategies within each subperiod with their characteristics in the full-sample dataset.

By providing a thorough interpretation of the momentum strategies' characteristics during both bear and bull market conditions, this study explains further the coefficients and variables through Figure 13 and Figure 14. Also, table 9 and Table 10 show the change in sensitivity from the market return on the return of each momentum strategy. From the regression equation 23 and equation 24, the research aims to investigate the features of all four-momentum monthly returns concerning the monthly market excess return. Furthermore, the paper will explore the interaction terms between the bear market indicator and the excess market return ($I_{Bear,t-1} \times R^e_{m,t}$) and between the bear market indicator, up-market indicator, and excess market return ($I_{Bear,t-1} \times I_{Up,t} \times R^e_{m,t}$). The purpose of analyzing the interaction term between the bear market indicator and the up-market indicator is to examine the effect of the contemporaneous market rebound during a bearish trend on the return of each momentum strategy. While both alphas and betas are crucial points, this paper will focus on beta as it shows the sensitivity or characteristics of each strategy, whereas alpha is typically discussed in the context of performance evaluation. Starting with the bear market,

The criteria for "bear indicator, $I_{Bear,t-1}$" and "up-market indicator, $\tilde{I}_{Up,t}$" are not the same. The reason for the bear indicator using 24 months past cumulative return is just to confirm the bearish trend for the previous month or month t-1. While the up-market indicator uses contemporaneous market return on this month t to show the market rebound within the bigger trend which in contrast to the bull markets.

Figure 13 The example of the SET index line chart during a bearish trend.
The figure above shows a blue line chart showing the SET index during the bearish trend, and the black lines are the parallel channel that indicates the support and resistance of this bear trend.

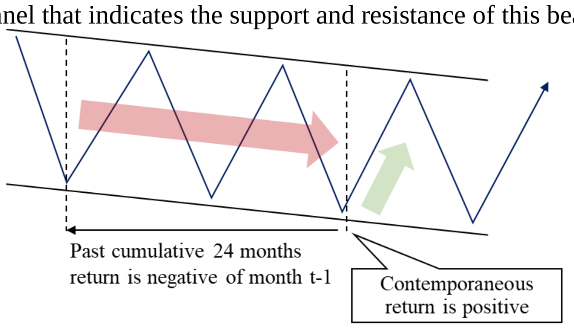


Table 9 The beta coefficients in each market condition for the bear market regression equation.
The table below shows the beta coefficients of the bear market regression equation during up- and down-trend markets and during market rebound and not rebound. The regression is as follows:

$$R_{i,t}^{e} = [\alpha_0 + \alpha_{Bear} I_{Bear,t-1}] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ +I_{Bear,t-1}I_{Up,t}\beta_{Bear,Up} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

	Rebound	Not rebound
Downtrend markets	$\beta_0 + \beta_{Bear} + \beta_{Bear,Up}$	$\beta_0 + \beta_{Bear}$
Uptrend markets	β_0	

The criteria for "bear indicator, $I_{Bull,t-1}$" and "down-market indicator, $I_{Down,t}$" are not the same. The reason for the bull indicator using 24 months past cumulative return is just to confirm the bullish trend for the previous month or month t-1. In comparison, the down-market indicator uses contemporaneous market return on this month t to show the market reversal in the bigger trend.

Figure 14 The example of the SET index line chart during a bearish trend.
The figure above shows a blue line chart showing the SET index during the bullish trend, in which the black lines are the parallel channel that indicates the support and resistance of this bull trend.

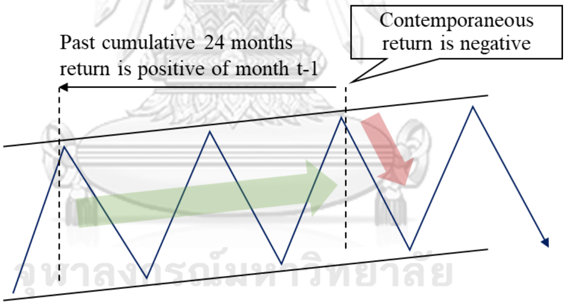


Table 10 The beta coefficients in each market condition for the bull market regression equation.
The table below shows the beta coefficients of the bull market regression equation during up- and down-trend markets and during market reverse and not reverse. The regression is as follows:

$$R_{i,t}^{e} = [\alpha_0 + \alpha_{Bull} I_{Bull,t-1}] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ +I_{Bull,t-1}I_{Down,t}\beta_{Bull,Down} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

	Reverse	Not reverse
Downtrend markets	β_0	
Uptrend markets	$\beta_0 + \beta_{Bull} + \beta_{Bull,Down}$	$\beta_0 + \beta_{Bull}$

5.5.1 Overall (from January 2013 to December 2022)

Section 5.5.1 is dedicated to examining the characteristics exhibited by all momentum strategies during the sample period, spanning from January 2013 to December 2022, which is defined as the full sample. The analysis entails a comprehensive exploration of these characteristics, and the corresponding coefficients from the regression equations are presented in Table 11. The characteristics identified in the full-sample period serve as a benchmark against which the time-varying characteristics can be compared. This benchmark allows for a meaningful evaluation and comparison of how the characteristics of the momentum strategies vary over time.

Overall, this study conducts regression analyses for various momentum strategies during different market conditions, namely bear markets, bull markets, and normal market conditions. The findings can be summarized as follows:

During bear markets, the sMOM strategy is the most effective, yielding a positive abnormal return of 0.6480% monthly above the market return, significant at the 10% level (t-statistic = 1.90028). This finding is consistent with Wang and Yan (2021), which suggests that sMOM performs well in managing downside risk. The other strategies, including dMOM and cMOM, show approximately zero abnormal returns as there is no statistical significance, indicating limited effectiveness during bearish periods. In normal market conditions, the standard MOM strategy exhibits higher sensitivity, significant at the 10% level. This is in line with the findings of Jegadeesh and Titman (1993), who reported the effectiveness of momentum strategies in general market conditions. Enhanced momentum strategies (dMOM, sMOM, and cMOM) display lower magnitudes of bear-market beta coefficients, suggesting reduced sensitivity relative to the standard MOM portfolio during bear markets. This is consistent with the findings of Hanauer and Windmüller (2023), who reported the benefits of enhanced momentum strategies and also consistent with the hypothesis that they exhibit consistent performance.

During bull markets, all strategies exhibit negative betas, significant at the 1% level, indicating a negative correlation with market returns. This could be attributed to the fact that momentum strategies tend to underperform during normal market conditions. Enhanced momentum strategies show lower magnitudes in betas compared to the standard MOM strategy, suggesting lower sensitivity during normal market conditions, which are consistent with Daniel and Moskowitz (2016) that momentum strategies show consistent positive performance across market conditions. All strategies display positive bull-market betas with statistical significance. Enhanced momentum strategies have lower magnitudes than the standard MOM approach, indicating higher sensitivity during bull markets, although less than the standard strategy. This is consistent with the findings of Barroso and Santa-Clara (2015), who reported that momentum strategies exhibit time-varying performance, especially in the constant volatility-scale momentum approach.

In summary, the analysis indicates that enhanced momentum strategies, particularly sMOM, perform better in bear markets with positive abnormal returns and lower sensitivity to market downturns. During bull markets, all strategies show positive sensitivity, with enhanced strategies exhibiting lower sensitivity compared to the standard MOM approach.

Table 11 The coefficient from the regression in the overall period.

The table shows the coefficients of the regression of monthly returns in the overall period of all four-momentum strategies (MOM, cMOM, sMOM, dMOM), the interaction of the bear market indicator and up-market indicator in the overall period ranges from January 2013 to December 2022. Panel A shows results for each of the momentum portfolios in bear markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bear} I_{Bear,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ + I_{Bear,t-1} I_{Up,t} \beta_{Bear,Up} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

During bull markets, $I_{B,t-1}$ is substituted with $I_{L,t-1}$ to analyze the impact of the market during these market conditions. Panel B shows results for each of the momentum portfolios in bull markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bull} I_{Bull,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ + I_{Bull,t-1} I_{Down,t} \beta_{Bull,Down} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

The estimated regression intercept or abnormal returns (α) are all multiplied by 100 to make them in percentage terms. The value in the parenthesis indicates the t-statistic of the coefficient. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *.

Coefficient	Momentum portfolio			
	MOM	cMOM	sMOM	dMOM
Panel A: Bear markets				
$\hat{\alpha}_0$	0.0740	0.3589	0.6480*	0.3031
	(0.3179)	(1.3171)	(1.9003)	(1.2474)
$\hat{\alpha}_{Bear}$	-0.1422	-0.2648	-0.5043	0.0201
	(-0.1873)	(-0.2977)	(-0.4531)	(0.0253)
$\hat{\beta}_0$	0.1151*	-0.0195	-0.0147	-0.0165
	(1.7057)	(-0.2466)	(-0.1488)	(-0.2336)
$\hat{\beta}_{Bear}$	-0.4735***	-0.3098*	-0.4388**	-0.3290**
	(-3.1569)	(-1.7634)	(-1.9962)	(-2.1005)
$\hat{\beta}_{Bear,Up}$	-0.2620	-0.1596	-0.0661	-0.2286
	(-1.3545)	(-0.7045)	(-0.2330)	(-1.1314)
Panel B: Bull markets				
$\hat{\alpha}_0$	-0.7521	-0.3225	-0.0288	-0.2734
	(-1.0590)	(-0.3887)	(-0.0277)	(-0.3688)
$\hat{\alpha}_{Bull}$	1.1393	1.0069	1.0155	0.8513
	(1.2805)	(0.9685)	(0.7810)	(0.9166)
$\hat{\beta}_0$	-0.5153***	-0.4249***	-0.4931***	-0.4824***
	(-5.5918)	(-3.9466)	(-3.6619)	(-5.0152)
$\hat{\beta}_{Bull}$	0.7453***	0.5248**	0.6027**	0.5668***
	(3.6363)	(2.1914)	(2.0120)	(2.6489)
$\hat{\beta}_{Bull,Down}$	-0.2261	-0.2348	-0.2444	-0.1983
	(-0.7277)	(-0.6469)	(-0.5384)	(-0.6115)

5.5.2 Before the COVID-19 pandemic (from January 2013 to March 2020)

Section 5.5.2 is dedicated to the thorough examination of the characteristics exhibited by all momentum strategies during the subsample period, extending from January 2013 to March 2020, which is defined as the period before the COVID-19 pandemic. The analysis involves an in-depth exploration of these characteristics, and the corresponding coefficient values from the regression analysis are presented in Table 12. Through this analysis, valuable insights are gained into the intricate relationships and dynamic interactions between the momentum strategies and market conditions during this subsample period. Before the COVID-19 pandemic, this research observed the following results for various momentum strategies during bear and bull market conditions:

During bear markets, all momentum strategies, including MOM, cMOM, sMOM, and dMOM, show positive monthly abnormal returns, with statistically significant values of 0.3564%, 0.7395%, 1.1219%, and 0.6244%, respectively. The standard MOM strategy's abnormal return is significant at the 10% level, while the other three enhanced momentum strategies have alphas significant at the 5% level. This indicates that all momentum approaches outperform the market during bear market states, and enhanced momentum strategies outperform the standard momentum in general. All momentum strategies bear-market betas have a negative sign, indicating a negative correlation with the market. Enhanced momentum strategies display lower magnitudes of bear-market beta coefficients, suggesting reduced sensitivity during bear markets. Only sMOM sensitivity is slightly different from MOM, but dMOM has lower sensitivity during this bear market state, while cMOM shows approximately zero correlation to the market return as it is not statistically significant. The sMOM approach adjusts the weight of its portfolio based on downside volatility by using an indicator that considers the momentum return for each day. When the past six-month volatility is low, it tends to increase the weight of that month, indicating that the past performance of the momentum strategy has been doing well. This approach is consistent with the findings of Wang and Yan (2021). Even if the momentum strategy is not performing well, the sMOM strategy adds weight at the right time, which can make it profitable as MOM returns are usually positive.

During bull markets, all strategies exhibit positive bull-market betas with statistical significance, indicating higher sensitivity during bull markets and generating positive returns as they follow the market. When the trend reverses, the negative down-market betas for MOM, cMOM, and dMOM illustrate that these strategies are less sensitive during the rebound, while sMOM maintains its positive sensitivity.

To sum up, comparing the sensitivity during bull and bear market conditions, momentum strategies generally create positive returns as they follow the market when it is bullish and move in the opposite direction when the market is bearish. Holding a momentum portfolio during a bullish market allows investors to enjoy the trend-following strategy. In contrast, during trend reversals, the sensitivity or risk reduces automatically. This reduction in sensitivity during trend reversals can be seen as a built-in risk management mechanism in momentum portfolios, which this consistence in performance in both markets aligns with the findings of Daniel and Moskowitz (2016) and consistent with the hypothesis that momentum strategies are robust across time. By automatically lowering the portfolio's exposure to market fluctuations during trend reversals, the risk of significant losses is reduced, allowing investors to protect their gains and potentially benefit from new market trends as they emerge. Furthermore, it is noteworthy that the characteristic of this subsample period is consistent with that of the full sample, with one notable exception. During bear market conditions, all momentum strategies demonstrate positive abnormal returns that are statistically significant.

Table 12 The coefficient from the regression before the COVID-19 pandemic.
The table shows the coefficients of the regression of monthly returns in the overall period of all four-momentum strategies (MOM, cMOM, sMOM, dMOM), the interaction of the bear market indicator and up-market indicator in the overall period ranges from January 2013 to December 2022. Panel A shows results for each of the momentum portfolios in bear markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bear} I_{Bear,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ +I_{Bear,t-1} I_{Up,t} \beta_{Bear,Up} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

During bull markets, $I_{B,t-1}$ is substituted with $I_{L,t-1}$ to analyze the impact of the market during these market conditions. Panel B shows results for each of the momentum portfolios in bull markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bull} I_{Bull,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ +I_{Bull,t-1} I_{Down,t} \beta_{Bull,Down} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

The estimated regression intercept or abnormal returns (α) are all multiplied by 100 to make them in percentage terms. The value in the parenthesis indicates the t-statistic of the coefficient. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *.

Coefficient	Momentum portfolio			
	MOM	cMOM	sMOM	dMOM
Panel A: Bear markets				
$\hat{\alpha}_0$	0.3564*	0.7395**	1.1219**	0.6244**
	(1.7455)	(2.3299)	(2.4217)	(2.3167)
$\hat{\alpha}_{Bear}$	-0.4329	-0.7483	-1.2486	-0.6782
	(-0.2913)	(-0.4929)	(-0.6757)	(-0.5260)
$\hat{\beta}_0$	0.1026	-0.0507	-0.0472	-0.0428
	(1.4748)	(-0.7137)	(-0.5454)	(-0.7096)
$\hat{\beta}_{Bear}$	-0.4275**	-0.2623	-0.4095*	-0.2696*
	(-2.3515)	(-1.4122)	(-1.8116)	(-1.7091)
$\hat{\beta}_{Bear,Up}$	2.3190	3.3681	4.2106	3.3006
	(0.7445)	(1.0586)	(1.0872)	(1.2215)
Panel B: Bull markets				
$\hat{\alpha}_0$	0.5486	0.8991	1.0083	0.8360
	(0.4080)	(0.5990)	(0.5199)	(0.6552)
$\hat{\alpha}_{Bull}$	0.5016	0.6213	0.9913	0.4479
	(0.3504)	(0.3888)	(0.4801)	(0.3298)
$\hat{\beta}_0$	-0.2695	-0.2326	-0.3562	-0.2336
	(-1.5973)	(-1.2348)	(-1.4634)	(-1.459)
$\hat{\beta}_{Bull}$	0.6089***	0.4484*	0.6085*	0.4158**
	(2.6374)	(1.9375)	(1.8273)	(1.9879)
$\hat{\beta}_{Bull,Down}$	-0.4679*	-0.5267*	-0.5920	-0.4447*
	(-1.7289)	(-1.7433)	(-1.5165)	(-1.8318)

5.5.3 One year after-COVID-19 pandemic (one year after the momentum crash ranging from April 2020 to April 2021)

Section 5.5.3 delves into a comprehensive examination of the characteristics exhibited by all momentum strategies during the subsample period, spanning from April 2020 to April 2021, which represents one year following the occurrence of the COVID-19 pandemic. The coefficient values derived from the regression equations are presented in Table 14, shedding further light on the characteristics and dynamics of the momentum strategies during this specific subsample period. During the 1-year period after the COVID-19 pandemic, this study observed the following results for various momentum strategies during bear and bull market conditions:

In bear markets, all strategies exhibit higher sensitivity than the market, with enhanced momentum portfolios showing even higher sensitivity than the standard MOM portfolio. This suggests that enhanced momentum strategies may respond more strongly to market fluctuations during bearish periods. MOM, cMOM, and sMOM display a negative correlation with the market, while dMOM does not. This indicates that dMOM follows the market during normal conditions, as opposed to other strategies that exhibit an inverse relationship with the market.

In bull markets, all strategies exhibit lower sensitivity than the market. However, enhanced momentum portfolios show higher sensitivity than the standard MOM portfolio during normal conditions. This suggests that enhanced momentum strategies may offer higher sensitivity and potential gain compared to the standard MOM approach. Similar to bear markets, MOM, cMOM, and sMOM show a negative correlation with the market, while dMOM does not. This again highlights that dMOM follows the market during normal conditions.

It is important to note that dMOM was specifically designed to tackle momentum crashes, and it performs well in the Stock Exchange of Thailand. This finding is consistent with Daniel and Moskowitz (2016) but not robust across the period as the hypothesis, which demonstrated the effectiveness of dMOM in mitigating momentum crashes. The observed performance of dMOM in this study lends further support to the benefits of using dMOM as a momentum strategy, particularly in the context of the Thai stock market. In contrast to the full sample analysis, the subsample period exhibits higher sensitivity and higher than the market during bear market states. This heightened sensitivity is particularly pronounced due to the significant impact of the COVID-19 pandemic, which resulted in a predominantly bearish trend throughout this subsample period. Additionally, these results show asymmetry characteristic in performance between bull and bear market as evidenced by Dobrynskaya (2014) that investors price the risk differently in both markets. Investors tend to take risk during the downturn of the market, while protect their wealth in market upturn making asymmetric in sensitivity occur.

Table 13 The coefficient from the regression one year after-COVID-19 pandemic.
The table shows the coefficients of the regression of monthly returns in the overall period of all four-momentum strategies (MOM, cMOM, sMOM, dMOM), the interaction of the bear market indicator and up-market indicator in the overall period ranges from April 2020 to April 2021. Panel A shows results for each of the momentum portfolios in bear markets, and the regression model is as follows:

$$R^e_{i,t} = \left[\alpha_0 + \alpha_{Bear} I_{Bear,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ +I_{Bear,t-1} I_{Up,t} \beta_{Bear,Up} \end{bmatrix} R^e_{m,t} + \epsilon_t$$

During bull markets, $I_{B,t-1}$ is substituted with $I_{L,t-1}$ to analyze the impact of the market during these market conditions. Panel B shows results for each of the momentum portfolios in bull markets, and the regression model is as follows:

$$R^e_{i,t} = \left[\alpha_0 + \alpha_{Bull} I_{Bull,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ +I_{Bull,t-1} I_{Down,t} \beta_{Bull,Down} \end{bmatrix} R^e_{m,t} + \epsilon_t$$

The estimated regression intercept or abnormal returns (α) are all multiplied by 100 to make them in percentage terms. The value in the parenthesis indicates the t-statistic of the coefficient. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *.

Coefficient	Momentum portfolio			
	MOM	cMOM	sMOM	dMOM
Panel A: Bear markets				
$\hat{\alpha}_0$	-1.1947	-1.5786	-0.9442	0.6798
	(-0.3917)	(-0.3900)	(-0.3142)	(0.2148)
$\hat{\alpha}_{Bear}$	0.0362	0.0175	0.0171	0.3514
	(0.0108)	(0.0039)	(0.0052)	(0.1012)
$\hat{\beta}_0$	-1.0202*	-1.5703**	-1.1893**	1.3846**
	(-1.7883)	(-2.0741)	(-2.1162)	(2.3397)
$\hat{\beta}_{Bear}$	0	0	0	0
	(-)	(-)	(-)	(-)
$\hat{\beta}_{Bear,Up}$	0.4296	0.7583	0.6019	-0.8430
	(0.6674)	(0.8877)	(0.9492)	(-1.2624)
Panel B: Bull markets				
$\hat{\alpha}_0$	-0.5755	-0.5320	-0.1102	-0.1128
	(-0.4117)	(-0.2844)	(-0.0858)	(-0.0818)
$\hat{\alpha}_{Bull}$	-0.6991	-1.1876	-0.9458	0.9493
	(-0.1530)	(-0.1942)	(-0.2251)	(0.2105)
$\hat{\beta}_0$	-0.6488***	-0.9148***	-0.6690***	0.6560***
	(-3.6018)	(-3.7949)	(-4.0393)	(3.6902)
$\hat{\beta}_{Bull}$	0	0	0	0
	(-)	(-)	(-)	(-)
$\hat{\beta}_{Bull,Down}$	0	0	0	0
	(-)	(-)	(-)	(-)

5.5.4 Two years after-COVID-19 (two years after the momentum crash ranging from April 2020 to December 2022)

Section 5.5.4 specifically focuses on the examination of the characteristics exhibited by all momentum strategies during a subsample period extending from April 2020 to December 2022, encompassing a two-year duration following the occurrence of the COVID-19 pandemic. To analyze these characteristics, regression equations 23 and 24 are employed, and the corresponding coefficient values are presented in Table 14. For the 2-year period after the COVID-19 pandemic, this study observed the following results for various momentum strategies during bear and bull market conditions:

In bear markets, all momentum strategies yield abnormal returns with statistical significance. However, MOM, cMOM, and sMOM generate negative abnormal returns at -1.1312%, -1.6168%, and -1.6023% per month, respectively, while dMOM shows a positive value of 1.2359% during normal conditions. This suggests that dMOM is more resilient during bearish periods. All enhanced strategies exhibit higher sensitivity than the market, with beta values above 1. Additionally, the enhanced momentum portfolio shows even higher sensitivity than the standard MOM portfolio.

In bull markets, all enhanced strategies display lower sensitivity than the market. Interestingly, all momentum portfolios show nearly the same sensitivity levels, as indicated by the similar magnitudes of beta values during normal conditions. This suggests that the strategies tend to move together during bullish periods.

After the COVID-19 pandemic, cMOM and sMOM underperform MOM in terms of both abnormal returns and sensitivity which is not consistent with Hanauer and Windmüller (2023). However, they tend to move together in general. This observation is consistent with Barroso and Santa-Clara (2015), who reported that momentum strategies exhibit time-varying performance. It is important to note that dMOM was specifically designed to tackle momentum crashes, and it performs well in the Stock Exchange of Thailand.

This finding is consistent with robustness characteristics and also in line with Daniel and Moskowitz (2016), who demonstrated the effectiveness of dMOM in mitigating momentum crashes. The observed performance of dMOM in this study lends further support to the benefits of using dMOM as a momentum strategy, particularly in the context of the Thai stock market. Additionally, the characteristics observed in this subsample are largely consistent with those of the full sample except for the abnormal return. In this subsample, MOM, cMOM, and sMOM strategies exhibit negative and statistically significant abnormal returns, whereas the dMOM strategy demonstrates positive abnormal returns. In contrast to the findings observed one year after the COVID-19 pandemic, the sensitivities of these momentum strategies remain lower but still greater than what shown in full-sample analysis. For empirical explanation, this increase in the sensitivity, especially in the bear market conditions, might occur form the deeply drop from the market which investors can view this situation as increasing in probability of the market rebound. This result is of asymmetric is consistent with one year after the crash. However, it indicates that the impact of the COVID-19 pandemic has been resolved to some extent during this subsample period.

Table 14 The coefficient from the regression two years after-COVID-19 pandemic.
The table shows the coefficients of the regression of monthly returns in the overall period of all four-momentum strategies (MOM, cMOM, sMOM, dMOM), the interaction of the bear market indicator and up-market indicator in the overall period ranges from April 2020 to December 2022. Panel A shows results for each of the momentum portfolios in bear markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bear} I_{Bear,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bear,t-1}\beta_{Bear} \\ +I_{Bear,t-1} I_{Up,t} \beta_{Bear,Up} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

During bull markets, $I_{B,t-1}$ is substituted with $I_{L,t-1}$ to analyze the impact of the market during these market conditions. Panel B shows results for each of the momentum portfolios in bull markets, and the regression model is as follows:

$$R_{i,t}^{e} = \left[\alpha_0 + \alpha_{Bull} I_{Bull,t-1}\right] + \begin{bmatrix} \beta_0 + I_{Bull,t-1}\beta_{Bull} \\ +I_{Bull,t-1} I_{Down,t} \beta_{Bull,Down} \end{bmatrix} R_{m,t}^{e} + \epsilon_t$$

The estimated regression intercept or abnormal returns (α) are all multiplied by 100 to make them in percentage terms. The value in the parenthesis indicates the t-statistic of the coefficient. Significant levels at 1 percent, 5 percent, and 10 percent are indicated, respectively, by ***, **, and *.

Coefficient	Momentum portfolio			
	MOM	cMOM	sMOM	dMOM
Panel A: Bear markets				
$\hat{\alpha}_0$	-1.1312*	-1.6168**	-1.6023**	1.2359*
	(-1.7348)	(-2.1769)	(-2.2006)	(1.8869)
$\hat{\alpha}_{Bear}$	0.2928	0.7905	0.9663	-0.4765
	(0.2148)	(0.5092)	(0.6349)	(-0.3480)
$\hat{\beta}_0$	0.1931	0.2618	0.2467	-0.2002
	(0.7654)	(0.9111)	(0.8755)	(-0.7897)
$\hat{\beta}_{Bear}$	-0.9605*	-1.1150*	-1.1147*	1.2001**
	(1.7984)	(-1.8330)	(-1.8692)	(2.2368)
$\hat{\beta}_{Bear,Up}$	0.2058	0.3050	0.3257	-0.4804
	(0.3767)	(0.4903)	(0.5340)	(-0.8755)
Panel B: Bull markets				
$\hat{\alpha}_0$	-0.5133	-0.3445	-0.1215	0.0006
	(-0.5123)	(-0.3019)	(-0.1087)	(0.0006)
$\hat{\alpha}_{Bull}$	-1.0268	-1.8192	-2.0539	1.6533
	(-0.6565)	(-1.0213)	(-1.1763)	(1.0444)
$\hat{\beta}_0$	-0.5949***	-0.5975***	-0.5950***	0.5972***
	(-4.5066)	(-3.9748)	(-4.0386)	(4.4705)
$\hat{\beta}_{Bull}$	0.5703	0.5683	0.5367	-0.5749
	(0.9734)	(0.8517)	(0.8206)	(-0.9695)
$\hat{\beta}_{Bull,Down}$	0.4194	0.5609	0.5878	-0.4287
	(0.4510)	(0.5295)	(0.5662)	(-0.4555)

CHAPTER 6
Conclusion

The aim of the current study become to look into the potential use of momentum techniques also investigate time-varying characteristics in the Stock Exchange of Thailand. It has two specific objectives. Firstly, it intends to contrast the performance of volatility-scaled momentum approaches with that of the traditional portfolio, focusing on long-term performance and transaction costs. It also seeks to investigate the dynamics of momentum techniques across time. The study will be conducted in two steps: analyzing strategy behavior before, during, and after crises, with a specific focus on momentum crashes, and exploring strategy behavior in bull and bear markets. While some strategies may not consistently outperform the standard momentum strategy in all market conditions, they may demonstrate different performance during bull periods or consistently outperform in all conditions.

This paper gives a thorough examination of the Thai Stock Market throughout January 2013 until December 2022. The study begins with construction of momentum portfolios following the methodologies proposed by Fama and French (2012, 2017) and Jegadeesh and Titman (1993). Building upon previous literature, the study enhances the momentum strategy by incorporating volatility measures, including constant volatility-scaled momentum (cMOM), constant semi-volatility-scaled momentum (sMOM), and dynamic volatility-scaled momentum (dMOM). Then, the performance and distribution characteristics of these momentum portfolios are thoroughly compared and analyzed. Additionally, the study identifies momentum crashes, which serve as criteria for dividing the full sample into subperiods for further analysis. Additionally, the study uses regression analysis to assess at the performance of the momentum portfolios over time, in both bullish and bearish markets, using market return as a regressor.

Our findings, consistent with our hypothesis and previous studies by Hanauer and Windmüller (2023), show that improved momentum methods boost profitability and Sharpe ratios significantly. Moreover, these strategies lead to a reduction in the magnitudes of skewness and kurtosis, indicating a more desirable return distribution.

Although higher moments of return decrease, maximum drawdowns do not follow these moments.

Focusing on the COVID-19 pandemic as the sampling period, this research found that this crisis caused substantial market drawdown and heightened volatility. Following a rebound after this bear market state, the winner-minus-loser momentum portfolio shows consistent negative returns where these periods of anomalies in momentum investing are termed momentum crashes by Daniel and Moskowitz (2016). This crash in the investment strategies period occurred when the pandemic began to affect Thailand in early 2020. The occurrence of this momentum crash period serves as a criterion for dividing the sampling period into pre-COVID-19 and post-COVID-19 periods.

Prior to the COVID-19 pandemic, all enhanced strategies consistently outperformed the standard momentum strategy (MOM), aligning with both the hypothesis and the full sample data. Following the momentum crash phase, however, only the dynamic method (dMOM) displays considerable improvements and yields large profits. This strategy effectively manages to scale by incorporating expected returns. In contrast, the other strategies move in tandem during this period, deviating from the hypothesis and the full-sample results. The momentum crash period, characterized by a severe decline in performance due to the impact of the pandemic, particularly affects these strategies. The findings for dMOM are evident referred from literature given by Daniel and Moskowitz (2016), as this strategy was specifically designed to address and scale momentum crashes.

Furthermore, this study analyzes the turnovers of weighted long-short portfolios across all momentum strategies, considering them as factors for calculating round-trip costs. In line with findings from Hanauer and Windmüller (2023), turnovers are comparatively low for non-U.S. samples. Notably, there is only a 5% likelihood that the standard momentum strategy will generate net positive profits. However, this is not the case for enhanced momentum approaches, which consistently demonstrate certainty in generating profits. These results support the hypothesis that the enhanced momentum strategies yield profits even after accounting for transaction fees.

To evaluate the asymmetry between bull and bear markets, this paper employs regression analysis, incorporating market indicators for bear, bull, bear-up, and bull-down periods. This analysis aims to assess the impact of estimated market return on all four-momentum strategies.

Overall, when comparing the sensitivity of momentum strategies during bull and bear market conditions, positive returns are generally observed. These strategies tend to align with the market when it is bullish and move in the opposite direction during bearish periods. Holding a momentum portfolio during a bullish market allows investors to benefit from the trend-following technique, which is comparable to Daniel and Moskowitz (2016), similar to the pre-pandemic period. Interestingly, before the COVID-19 pandemic, momentum portfolios exhibited a reduction in sensitivity or risk automatically during trend reversals. This built-in risk management mechanism can be viewed as a characteristic of momentum portfolios. This behavior remained consistent with the pre-pandemic period. In contrast, one year following the recognition of COVID-19 on the Thai stock exchange, only the dynamic-scaled momentum strategy (dMOM) demonstrated positive abnormal returns with statistical significance, while the other strategies displayed negative abnormal returns and exhibited similar movements. However, their sensitivity was relatively high compared to other periods. On the other hand, two years after the COVID-19 disease outbreak, market characteristics were similar to those before the crisis, except for the standard momentum strategy (MOM), constant volatility-scaled momentum (cMOM), and constant semi-volatility-scaled momentum (sMOM), which experienced negative abnormal returns due to the crisis. At last, the sensitivity results support the hypothesis that these momentum strategies were robust across market conditions before the COVID-19 pandemic and two years after the pandemic. However, this robustness was not observed one year after the crisis, indicating a temporary deviation from the hypothesis during that specific period, which these results show asymmetry characteristic in performance between bull and bear market as evidenced by Dobrynskaya (2014).

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