

Can Thai mutual fund investors benefit from volatility managed? Evident from Thailand



Mr. Nattapong Shutimayotingul

An Independent Study Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Finance
Department of Banking and Finance
Faculty of Commerce and Accountancy
Chulalongkorn University
Academic Year 2024

นักลงทุนกองทุนรวมไทยสามารถได้รับประโยชน์จากการบริหารความผันผวนได้หรือไม่?
หลักฐานจากประเทศไทย



สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2567

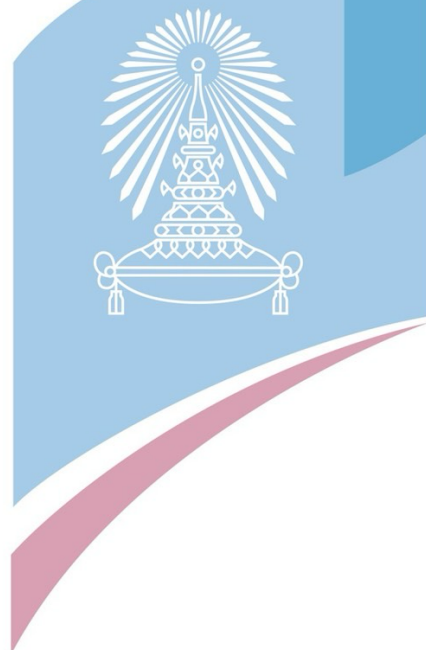
III

Independent Study Title	Can Thai mutual fund investors benefit from volatility managed? Evident from Thailand
By	Mr. Nattapong Shutimayotingul
Field of Study	Finance
Thesis Advisor	Anirut Pisedtasalasai

Accepted by the Faculty of Commerce and Accountancy, Chulalongkorn University in
Partial Fulfillment of the Requirement for the Master of Science

Independent Study Committee

.....	Advisor
(Anirut Pisedtasalasai)	
.....	Committee
(Tanakorn Likitapiwat)	
.....	Committee
(Jananya Sthienchoak)	



คำสำคัญ: การบริหารความผันผวน
 ณัฐพงษ์ ชุตินิมาโยธินกุล : นักลงทุนกองทุนรวมไทยสามารถได้รับประโยชน์จากการบริหารความผันผวนได้หรือไม่? หลักฐานจากประเทศไทย (Can Thai mutual fund investors benefit from volatility managed? Evident from Thailand) อาจารย์ที่ปรึกษาหลัก: อนิรุต พิเสฏฐธศลาศัย

งานวิจัยนี้ศึกษาว่านักลงทุนกองทุนรวมไทยสามารถได้รับประโยชน์จากกลยุทธ์การบริหารความผันผวนหรือไม่ โดยใช้ข้อมูลกองทุนรวมหุ้นไทยแบบเปิดตั้งแต่เดือนมกราคม 2548 ถึงธันวาคม 2567 การศึกษานี้ตรวจสอบว่ากลยุทธ์การบริหารความผันผวนช่วยปรับปรุงผลตอบแทนที่ปรับตามความเสี่ยงในกองทุนจัดการทั้งแบบเชิงรุกและเชิงรับหรือไม่ วิเคราะห์ปัจจัยขับเคลื่อนผลการดำเนินงานผ่านการจับจังหวะความผันผวนและการจับจังหวะผลตอบแทน และวิเคราะห์ว่านักลงทุนนำกลยุทธ์เหล่านี้ไปใช้ในทางปฏิบัติผ่านพฤติกรรมกระแสเงินเข้าออกกองทุนหรือไม่

ผลการศึกษาพบว่ากลยุทธ์การบริหารความผันผวนช่วยปรับปรุงผลการดำเนินงานที่ปรับตามความเสี่ยงและสามารถรับมือกับต้นทุนการทำธุรกรรมได้ แต่มีประสิทธิภาพในบางช่วงสภาวะตลาดที่เฉพาะเจาะจงเท่านั้น นักลงทุนกองทุนรวมไทยแสดงให้เห็นถึงความเข้าใจในประโยชน์ของการบริหารความผันผวน ซึ่งปรากฏจากการลดสัดส่วนการลงทุนเมื่อความผันผวนสูงขึ้นในทุกรูปแบบการวัดความผันผวน

สาขาวิชา การเงิน
 ปีการศึกษา 2567

ลายมือชื่อ นิสิต.....
 ลายมือชื่อ อ.ที่ปรึกษาหลัก.....
 ลายมือชื่อ อ.ที่ปรึกษาร่วม.....
 ลายมือชื่อ อ.ที่ปรึกษาร่วม.....

6784033826 : MAJOR FINANCE

KEYWORDS: Volatility managed

Nattapong Shutimayotingul : Can Thai mutual fund investors benefit from volatility managed? Evident from Thailand Advisor: Anirut Pisedtasalasai

This paper examines whether Thai mutual fund investors can benefit from volatility-managed strategies using Thai open-ended domestic equity funds from January 2005 to December 2024. The study investigates whether volatility-managed strategies improve risk-adjusted returns across both active and passive funds, examines the performance drivers through volatility timing and return timing analysis, and analyzes whether investors implement these strategies in practice through fund flow behavior.

The results show that volatility-managed strategies improve risk-adjusted performance and survive transaction costs but only work effectively during specific market conditions. Thai mutual fund investors demonstrate awareness of volatility timing benefits, as evidenced by reducing fund positions when volatility is high across all volatility measures.

Field of Study Finance
Academic Year 2024



Student's Signature.....
Advisor's Signature.....
Co-advisor's Signature.....
Co-advisor's Signature.....

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Associate Professor Anirut Pisedtasalasai, Ph.D., for his invaluable guidance and support throughout this research. I am also grateful to my committee members, Assistant Professor Jananya Sthienchoak, Ph.D., and Assistant Professor Tanakorn Likitapiwat, Ph.D., for their constructive feedback and assistance.

Special thanks to the FinLab officers for their help in accessing the Morningstar Direct database, and to my MSF full-time 28 classmates for their friendship and encouragement. I am particularly grateful to Suparek Saardeiam for being a patient listener and discussion partner whenever I was stuck during the research process.



Nattapong Shutimayotingul

TABLE OF CONTENTS

	Page
ABSTRACT (THAI)	IV
ABSTRACT (ENGLISH).....	V
ACKNOWLEDGEMENTS	VI
TABLE OF CONTENTS.....	VII
Abstract	1
1. INTRODUCTION	2
2. LITERATURE REVIEW	5
2.1 Volatility timing	5
2.2 Volatility-Managed Strategies	6
2.3 Downside Volatility Management.....	6
2.4 Volatility Management in Mutual Funds.....	6
3. Data	7
3.1. Data sample	7
3.2 Variables.....	8
3.2.1 The Computation of Fund Return.....	8
3.2.2 Risk Factor Construction	9
3.2.3 Fund flow calculation	10
3.2.4 Control variable calculation.....	10
3.3 Data Descriptive	11
4.METHODOLOGY	13
4.1 Estimated realized volatility.....	14
4.2 Construct Volatility managed strategy	15

4.3 Examining fund risk-adjusted performance	17
4.4 Comparison of performance of volatility-managed strategies across market conditions.....	19
4.5 Comparison of performance of volatility-managed strategies between actively managed and passively managed mutual funds.....	20
4.6 Examining volatility timing and return timing	20
4.7 Examining Fund flow.....	22
5. Empirical result	23
5.1 Baseline Analysis	23
5.2 Sub-period Analysis	25
5.3 Sharpe Ratios and Sortino Ratios	28
5.4 Transaction Costs Analysis.....	30
5.5 Source of Performance Gains	32
5.6 Fund Flows and Volatility.....	35
6. Conclusion	37
REFERENCES.....	39
AUTHOR BIOGRAPHY	1



Abstract

This paper examines whether Thai mutual fund investors can benefit from volatility-managed strategies using Thai open-ended domestic equity funds from January 2005 to December 2024. The study investigates whether volatility-managed strategies improve risk-adjusted returns across both active and passive funds, examines the performance drivers through volatility timing and return timing analysis, and analyzes whether investors implement these strategies in practice through fund flow behavior.

The results show that volatility-managed strategies do not universally improve performance but depend on period-specific market conditions. The effectiveness depends on return timing, which varies across market conditions and is the key driver of these strategies. Sub-period analysis reveals that during some periods and certain crisis events, both total and downside volatility-managed strategies significantly outperform unmanaged strategies. During favorable periods, these strategies enhance risk-adjusted performance across alpha, Sharpe ratios, and Sortino ratios, and survive transaction costs. This period-dependent effectiveness contrasts with prior studies that documented consistent positive performance throughout their sample periods. Thai mutual fund investors demonstrate awareness of volatility timing benefits by reducing positions when volatility is high across all volatility measures.

1. INTRODUCTION

Timing strategies form a crucial part of investment management, particularly in mutual funds where investors seek to optimize their risk-adjusted returns. Among these, volatility timing has gained increasing attention in recent years. Volatility-managed strategies stem from the work of Fleming et al. (2001, 2003), who show that volatility timing strategies deliver significant economic benefit to investors. By adjusting portfolio positions based on predicted volatility, investors can enhance Sharpe ratios and utility gains even after accounting for trading costs.

Later, Moreira and Muir (2017) find that managed portfolios that take less risk when volatility is high generate higher alphas, increase Sharpe ratios and produce large utility gains for mean-variance investors. Their evidence shows these benefits exist because changes in volatility are not offset by proportional changes in expected returns.

Recent studies document the economic value of volatility-managed strategies on various equity portfolios in the U.S. market. For example, Barroso and Santa-Clara (2015) improve momentum strategies by managing volatility of momentum to prevent crashes and increase Sharpe ratios. Barroso and Maio (2017) demonstrate that volatility timing enhances the performance of the betting-against-beta factor, leading to improved Sharpe ratios and reduced tail risk. Additionally, Eisdorfer and Misirli (2020) show similar benefits when applying volatility management to the financial distress factor. However, Cederburg et al. (2020) find the effectiveness of volatility timing is not universal across all investment strategies. The researchers examine a comprehensive set of 103 equity factors and document mixed performance results when implementing volatility management in real time. Later, Barroso and Detzel (2021) find the benefit of volatility managed cannot survive after accounting for transaction costs.

These prior studies primarily focus on equity factor portfolios, which are not directly tradable investment vehicles. Wang et al. (2021) extend this research by examining volatility-managed strategies in equity mutual funds, which are accessible to individual investors. Volatility-managed strategies can be done by investors which increase (decrease) their investment in mutual funds when past volatility is low (high). Their study finds that volatility-managed mutual funds outperform unmanaged funds

in term of risk-adjusted return, with downside volatility management showing even greater improvement than total volatility management. Additionally, their evidence suggests that U.S. mutual fund investors recognize the benefits of volatility timing and actively implement these strategies.

Unlike developed markets, the Chinese fund market exhibits several distinguishing characteristics that make volatility management particularly interesting to study. Zhang et al. (2024) find that actively managed mutual funds in China outperform their benchmarks, with over 90% of funds showing positive alphas. This differs significantly from the U.S. market where most active funds underperform. Additionally, the Chinese fund market is dominated by individual investors, who hold more than 80% of fund shares. These investors typically have limited investment experience and assets, making it difficult for them to use derivatives for risk management. In such an individual-dominated market, volatility management could offer an efficient tool for risk control.

This study examines volatility-managed strategies in the Thai mutual fund market. The objectives can be divided into three parts. The first objective investigates whether volatility-managed strategies improve Thai mutual fund investors' investment risk-adjusted returns. Volatility-managed strategies involve increasing investment when past fund volatility is low and decreasing positions when volatility is high. Following Wang et al. (2021) methodology, this study examines both total and downside volatility-managed strategies. The study analyzes two subperiods, which are a bull market (January 2005 - December 2014) and a bear market (January 2015 - December 2024) to examine strategy effectiveness across different market conditions. Performance is measured using Sharpe ratios, Sortino ratios, and Fama-French five-factor model alphas. The analysis includes subsamples of both actively and passively managed funds. The study incorporates realistic trading costs to ensure practical applicability. Based on prior evidence, volatility-managed strategies are hypothesized to outperform unmanaged buy-and-hold strategies.

The second objective investigates the key performance drivers for volatility managed strategies. Following Wang et al. (2021), two potential drivers volatility timing and return timing are tested. For volatility timing, the relationship between past

fund volatility and current volatility are analyzed. For return timing, the relationship between past fund volatility and current return are examined. This helps understand whether performance improvements come from avoiding periods of high volatility, low returns, or both.

The third objective investigates whether volatility-managed strategies is implemented by mutual fund investors in Thailand. The relationship between fund flows and past volatility provides insights into whether investors recognize and act on volatility signals when making investment decisions. This analysis is particularly relevant given Thailand's distinct investor composition and market characteristics. While developed markets show evidence that fund flow decreases when volatility is high (Wang et al., 2021), emerging markets with high retail participation may exhibit different patterns.

This study contributes to the existing literature in several ways. First, extending prior studies that focus primarily on developed markets and actively managed mutual funds, this research comprehensively examines volatility-managed strategies across both active and passive funds during different market conditions, particularly through a bull market period (January 2005 - December 2014) and a bear market period (January 2015 - December 2024). This provides unique insights into how management styles and market environments affect volatility timing benefits. Active funds, with their higher volatility from discretionary trading, may present different opportunities for volatility management compared to passive funds that track market indices. Additionally, examining performance across bull and bear market periods reveals how different market conditions influence the effectiveness of volatility-managed strategies, as the relationship between past volatility and future returns may vary significantly across different business cycles and market conditions.

Second, the Thai market offers a distinct setting for examining volatility management effectiveness. Unlike developed markets such as the US and Chinese markets, which experienced decade-long bull market conditions during previous studies (Wang et al., 2021; Zhang et al., 2024), the Thai market includes both extended bull and bear market periods. Thailand's market also features a larger proportion of retail investors compared to institutional investor-dominated developed markets, with

potentially different risk management capabilities. This unique combination of varying market conditions and investor composition provides an ideal setting to examine whether volatility-managed strategies are universally effective or depend on underlying market trends and investor behavior.

Third, examining performance across bull and bear market periods, and between active and passive funds, provides comprehensive evidence on whether the benefits of volatility management are universal or vary with market conditions and fund management approaches. This contributes to understanding how volatility-managed strategies can be effectively implemented in emerging markets with high retail investor participation.

The rest of this paper is organized as follows. Chapter 2 reviews the literatures relevant to this study which summarizes the previous empirical research. Chapter 3 describes the data and variables used in this paper. Chapter 4 describes the methodology and equations used in this study. Finally, Chapter 5 presents the empirical results of this study. Finally, Chapter 6 presents the conclusion of this study.

2. LITERATURE REVIEW

2.1 Volatility timing

Volatility timing represents a fundamental strategy in portfolio management where investors adjust their positions based on predicted volatility levels. Fleming et al. (2001, 2003) show that adjusting portfolio positions based on conditional covariances can enhance portfolio performance. Using high-frequency data to estimate volatility and correlation matrices, they find significant economic value in volatility timing strategies even after accounting for transaction costs.

Moreira and Muir (2017) advance this research by documenting that managed portfolios that take less risk when volatility is high generate higher alphas and increase Sharpe ratios. Their key finding is that changes in volatility are not offset by proportional changes in expected returns.

2.2 Volatility-Managed Strategies

Recent studies examine volatility-managed strategies across various investment contexts. Barroso and Santa-Clara (2015) show that managing the risk of momentum strategies by scaling monthly returns by the inverse of their realized volatility substantially reduces crash risk while maintaining high average returns. Barroso and Maio (2017) find similar benefits when applying volatility timing to the betting-against-beta factor. Eisdorfer and Misirli (2020) demonstrate that volatility management improves the performance of the financial distress factor.

However, Cederburg et al. (2020) challenge the universal effectiveness of these strategies. Examining 103 equity characteristics, they find mixed performance results when implementing volatility management in real time. Barroso and Detzel (2021) further question the practical benefits by showing that transaction costs can significantly impact strategy profitability.

2.3 Downside Volatility Management

The focus on downside volatility stems from evidence that downside risk may be priced differently from upside risk. Patton and Sheppard (2015) find that negative return volatility has stronger predictive power for future volatility than positive return volatility. Wang et al. (2021) extend this to mutual funds, showing that scaling by downside volatility leads to greater performance improvements than using total volatility.

2.4 Volatility Management in Mutual Funds

While early studies of volatility-managed strategies focused on equity factor portfolios, recent research extends these approaches to mutual funds, which represent directly investable assets for individual investors. This extension to mutual funds is particularly relevant as it tests whether the theoretical benefits of volatility management can be realized in actual investment vehicles.

Wang et al. (2021) provide the first comprehensive examination of volatility-managed strategies in mutual funds using U.S. market data. Their study finds that volatility-managed mutual funds significantly outperform unmanaged funds, with

improvements in both alphas and Sharpe ratios. They also document that downside volatility management provides even greater benefits than total volatility management in the mutual fund context. Importantly, their evidence suggests U.S. mutual fund investors recognize these benefits, as indicated by the relationship between fund flows and past volatility.

The effectiveness of these strategies extends to emerging markets. Zhang et al. (2024) examine volatility management in Chinese mutual funds, where market dynamics differ significantly from developed markets. In the Chinese market, which is dominated by individual investors who hold more than 80% of fund shares, they find that actively managed funds generally outperform their benchmarks. Their study shows that volatility-managed strategies can further enhance this performance, though individual investors appear less likely than institutions to implement volatility timing.

The application of volatility management to mutual funds remains an active area of research, particularly as evidence emerges from different market contexts and investor types. Understanding how these strategies perform across different market structures and investor compositions continues to be crucial for both academic research and practical investment management.

3. Data

3.1. Data sample

To investigate whether Thai mutual fund investors can improve their investment performance from volatility-managed strategies, this study examines a comprehensive sample of Thai open-end domestic equity funds from 2005 to 2024 using Morningstar Direct data. The analysis focuses on funds where volatility management can be practically implemented by investors. My sample data exclude tax-saving funds (Long-term equity funds, Super savings funds, Retirement mutual Funds, and ESG funds) due to their trading restrictions that would limit investors' ability to adjust positions based on volatility signals. To ensure proper implementation of volatility management strategies, the sample excludes funds with less than 80% equity exposure and those with trading history shorter than 12 months. To access investors' performance, Net asset values (NAV) and return data are obtained from Morningstar Direct. Funds are

classified as active or passive based on their stated investment objectives and fund names, allowing examination of how volatility management benefits vary across different investment styles.

Risk factors to examine risk-adjusted performance are obtained from the Thailand Capital Market Research Institute (CMRI)'s factor library (Charoenwong et al., 2021). A range of asset pricing models is employed for testing the volatility-managed strategies: CAPM one-factor model, Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model. The market factor (MKT), size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (CMA) are sourced directly from the CMRI factor library, where these factors are constructed specifically for the Thai market.

Fund characteristics serve as control variables to study the relationship between fund flows and past volatility. The key fund characteristics include total, total net assets (TNA), and fund age. Total net assets are collected from Morningstar Direct, while fund age is calculated based on the length of time each fund has been traded.

3.2 Variables

3.2.1 The Computation of Fund Return

Fund returns in this study serve two main purposes. The first purpose is studying the volatility managed strategy while the second purpose examines the relationship between fund flow and past volatility. I use daily raw returns to calculate realized volatility and monthly returns to calculate fund excess returns for testing risk-adjusted performance through Sharpe ratio, Sortino ratio, and Fama-French 5-factor's alpha. Morningstar Direct calculates fund gross return by using the change in a fund's NAV adjusted by dividend distribution divided by the initial NAV as equation

$$\text{return}_{i,t} = \frac{\text{NAV}_{i,t} + \text{DIV}_{i,t}}{\text{NAV}_{i,t-1}} - 1 \quad (1)$$

where $\text{return}_{i,t}$ is the raw return of the fund i at period t . $\text{NAV}_{i,t}$ is the net asset value of fund i at period t . $\text{DIV}_{i,t}$ is the dividend distribution of fund i at period t . $\text{NAV}_{i,t-1}$ is the net asset value of fund i at period $t-1$.

3.2.2 Risk Factor Construction

I obtain risk factors data from the Thailand Capital Market Research Institute (CMRI) factor library. The market risk premium (MRT) calculation uses SET TRI return and subtracts the risk-free rate as equation (2)

$$\text{MRT}_t = r_{m,t} - r_{f,t} \quad (2)$$

where $r_{m,t}$ is SET monthly total return at month t . $r_{f,t}$ is the 1-month Treasury Bill rate of Thailand at month t .

The size factor (SMB) calculation follows equation (3). CMRI first divides stocks in SET index into two size groups using the 50th percentile market capitalization as the breakpoint, forming small (S) and big (B) portfolios. Within each size group, stocks are further sorted into three book-to-market portfolios using the 30th and 70th percentiles as breakpoints, creating low (L), middle (M), and high (H) portfolios. This forms six portfolios: S/L, S/M, S/H, B/L, B/M, and B/H.

$$\text{SMB}_t = \frac{\text{S/L}_t + \text{S/M}_t + \text{S/H}_t}{3} - \frac{\text{B/L}_t + \text{B/M}_t + \text{B/H}_t}{3} \quad (3)$$

The value factor (HML) is constructed using equation (4), representing returns from buying high book-to-market stocks and selling low book-to-market stocks:

$$\text{HML}_t = \frac{\text{S/H}_t + \text{B/H}_t}{2} - \frac{\text{S/L}_t + \text{B/L}_t}{2} \quad (4)$$

Following Fama and French (2015), the profitability factor (RMW) and investment factor (CMA) are constructed using similar portfolio sorting methods follow equation (5) and (6). The RMW factor captures the outperformance of robust versus weak gross profitability companies, while the CMA factor represents the outperformance of conservative versus aggressive investment companies. Stock Exchange of Thailand (SET) sorts and ranks its listed stocks based on profitability and investment characteristics.

First, stocks in SET are independently sorted by size into small (S) and big (B) portfolios using the 50th percentile market capitalization breakpoint. These stocks are

then independently sorted by profitability into robust (R) and weak (W) portfolios, and by investment rates into conservative (C) and aggressive (A) portfolios, using the 50th percentile of each characteristic. The intersection of these sorts produces eight portfolios: S/R, S/W, S/C, S/A, B/R, B/W, B/C, and B/A. The factors are then calculated as:

$$RMW_t = \frac{S/R_t + B/R_t}{2} - \frac{S/W_t + B/W_t}{2} \quad (5)$$

$$CMA_t = \frac{S/C_t + B/C_t}{2} - \frac{S/A_t + B/A_t}{2} \quad (6)$$

where S/R and B/R represent the returns on robust profitability portfolios, S/W and B/W represent weak profitability portfolios, S/C and B/C represent conservative investment portfolios, and S/A and B/A represent aggressive investment portfolios.

3.2.3 Fund flow calculation

To study the relationship between fund flows and past volatility, I follow the standard approach in mutual fund literature Sirri and Tufano (1998). Fund flow is calculated as the percentage growth in fund assets beyond the growth that would have occurred from earning the fund's return. Specifically, fund flow is measured as the change in TNA adjusted for fund returns, normalized by the previous month's TNA as equation (7)

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})}{TNA_{i,t-1}} \quad (7)$$

Where $Flow_{i,t}$ is a monthly fund flow of fund i at period t , $TNA_{i,t}$, and $TNA_{i,t-1}$ are total net assets of fund i at period month t , and $t-1$.

3.2.4 Control variable calculation

Following Wang et al. (2021), I include several fund characteristics as control variables. The first control variable measures fund age, calculated as the time elapsed since the fund's inception (8)

$$\text{Age}_{i,t} = \text{Period}_{i,t} - \text{Inception Date}_i \quad (8)$$

where $\text{Age}_{i,t}$ represents the number of years fund i has been trading at month t . $\text{Period}_{i,t}$ is date that the fund i traded at month t . Inception Date_i is the initial listing date of fund i .

The second control variable is fund size, measured by the natural logarithm of total net assets (TNA). This transformation helps address the skewness in fund size distribution commonly observed in mutual fund data.

3.3 Data Descriptive

This study examines 277 Thai open-ended domestic equity mutual funds during the period 2004 to 2023, consisting of 250 actively managed funds and 27 passively managed funds. A summary statistic of key variable is presented in table 1.

According to Panel A, the average monthly fund return is 0.44% (5.28% p.a.) with a standard deviation of 4.85%. The average monthly risk-free rate is 0.16% (1.92% p.a.) with a standard deviation of 0.09%. As shown in Panel B, the average monthly total volatility is 4.25% (14.72% p.a.) with a standard deviation of 2.51%, while the average monthly downside volatility is 2.90% (10.04% p.a.) with a standard deviation of 2.08%.

When examining different market conditions across Panel A and Panel B, the pre-2015 period represents more favourable bull market conditions with higher average monthly returns of 1.17% (14.04% p.a.) compared to the post-2015 period of 0.12% (1.44% p.a.), which indicates more challenging bear market conditions. This pattern is consistent with higher volatility levels during the bull market period, where total volatility averaged 5.54% monthly (19.18% p.a.) in pre-2015 compared to 3.69% monthly (12.77% p.a.) during the bear market period post-2015.

Table 1: Summary statistics of equity mutual fund samples.

This table represents the summary statistics for Thai passive and active open-ended domestic equity mutual funds from 2004 to 2023, including number of observations (N), average (Mean), standard deviation (S.D.), minimum value (Min), and maximum value (Max). Panel A reports fund returns, which includes monthly raw returns and excess return calculated as the difference between monthly fund raw return across different time periods including all sample, pre-2015, post-2015. Panel B reports realized volatility measures, including total volatility computed from daily fund returns and downside volatility measured using negative daily returns.

Panel A: Monthly fund return

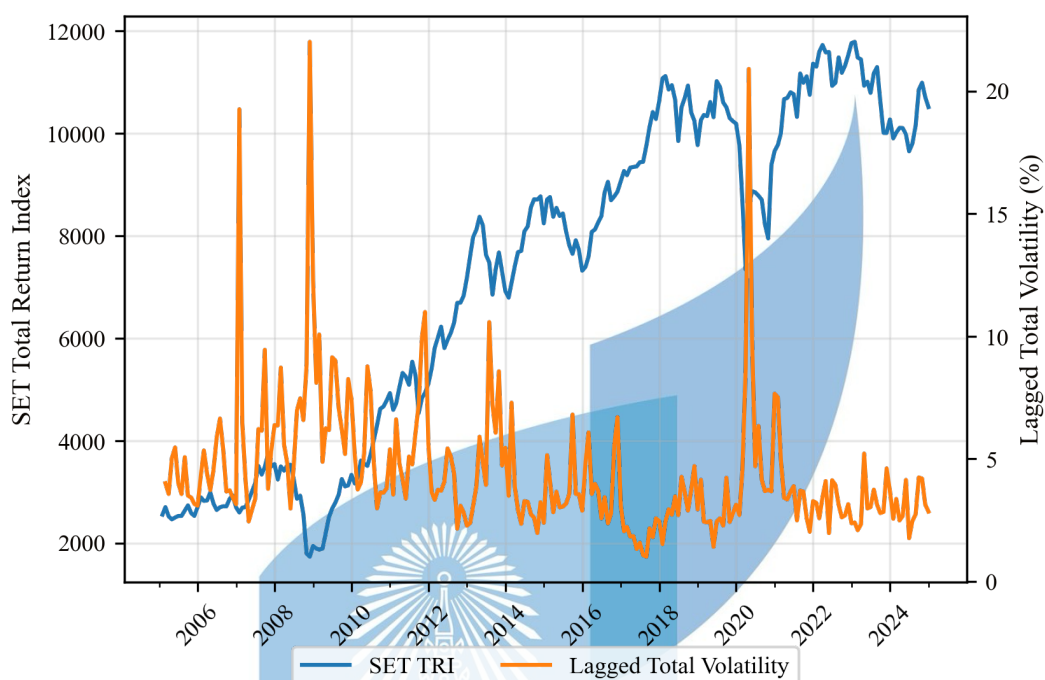
Variables	Period	Investment Strategy	N	Mean	Std.Dev.	Min	Max
Monthly fund return (% per month)							
	All sample	All	35,201	0.44%	4.85%	-31.29%	25.89%
		Active	31,700	0.43%	4.83%	-31.29%	25.89%
		Passive	3,501	0.51%	5.10%	-30.83%	23.62%
	Pre-2015	All	10,684	1.17%	5.99%	-31.29%	19.39%
		Active	9,562	1.17%	5.96%	-31.29%	19.39%
		Passive	1,122	1.19%	6.23%	-30.83%	17.02%
	Post-2015	All	24,517	0.12%	4.23%	-23.97%	25.89%
		Active	22,138	0.11%	4.20%	-23.97%	25.89%
		Passive	2,379	0.18%	4.44%	-18.80%	23.62%

Panel B: Realized Volatility

Variables	Period	Investment Strategy	N	Mean	Std.Dev.	Min	Max
Total Volatility (% per month)							
	All sample	All	35,195	4.25%	2.51%	0.02%	43.05%
		Active	31,694	4.23%	2.48%	0.02%	43.05%
		Passive	3,501	4.46%	2.78%	1.06%	25.66%
	Pre-2015	All	10,680	5.54%	2.93%	0.02%	43.05%
		Active	9,558	5.51%	2.91%	0.02%	43.05%
		Passive	1,122	5.79%	3.09%	2.06%	25.66%
	Post-2015	All	24,515	3.69%	2.07%	0.22%	25.33%
		Active	22,136	3.68%	2.03%	0.22%	25.33%
		Passive	2,379	3.83%	2.37%	1.06%	23.93%
Downside Volatility (% per month)							
	All sample	All	35,193	2.90%	2.08%	0.01%	27.17%
		Active	31,692	2.89%	2.06%	0.01%	27.17%
		Passive	3,501	3.01%	2.27%	0.42%	22.00%
	Pre-2015	All	10,678	3.66%	2.49%	0.01%	27.17%
		Active	9,556	3.64%	2.47%	0.01%	27.17%
		Passive	1,122	3.82%	2.64%	0.50%	22.00%
	Post-2015	All	24,515	2.57%	1.78%	0.13%	21.37%
		Active	22,136	2.56%	1.76%	0.13%	21.37%
		Passive	2,379	2.63%	1.96%	0.42%	20.31%

Figure 1: SET total return index and lagged realized market volatility, January 2005–December 2024

This figure displays the SET Total Return Index (left axis) and one-month lagged realized market volatility (right axis) over the sample period from January 2005 to December 2024.



According to Figure 1, shows the relationship between lagged market volatility and SET Total Return Index performance over the sample period. The graph demonstrates that high volatility periods typically signal poor market performance, while low volatility periods are associated with market gains. During the 2008 financial crisis and 2020 Covid-19 pandemic, spikes in lagged volatility above 20% coincided with significant market declines. Conversely, when volatility remained low, the SET index showed steady upward, indicating a negative relationship between past volatility and future returns. However, this relationship may vary across different market conditions.

4.METHODOLOGY

The methodology examines performance benefits of volatility-managed strategies through total and downside volatility measures in the Thai mutual fund

market context. Following Wang et al. (2021), fund returns are managed using volatility signals to assess risk-adjusted performance improvements. The analysis extends to both active and passive funds, providing comprehensive evidence of volatility management benefits across different fund styles. Based on the research objectives, the methodology addresses three main aspects: the evaluation of risk-adjusted performance improvements through selected measures, the examination of performance gain sources, and the investigation of fund flow responses to volatility as evidence of strategy implementation by investors. The testing methodology is divided into the following sections.

4.1 Estimated realized volatility

For implementing volatility-managed strategies, I first compute both total and downside realized volatility measures. Following Ghysels et al. (2005), I estimate total realized volatility as the square root of the sum of squared daily returns within each month.

$$\hat{\sigma}_{\text{Total},t} = \sqrt{\frac{22}{N_t} \sum_{d=1}^{N_t} (r_{t,d})^2} \quad (9)$$

where $\hat{\sigma}_{\text{Total},t}$ is the estimated fund's total realized volatility at month t . $r_{t,d}$ represents the fund's daily raw return, and N_t is the actual number of trading days in month t .

For downside volatility, following Barndorff-Nielsen et al. (2010), I calculate realized downside volatility similarly to total volatility but consider only negative return.

$$\hat{\sigma}_{\text{Down},t} = \sqrt{\frac{22}{N_t} \sum_{d=1}^{N_t} (r_{t,d})^2 I_{[r_{t,d} < 0]}} \quad (10)$$

where $\hat{\sigma}_{\text{down},t}$ is the estimated fund's downside realized volatility at month t . $r_{t,d}$ is the fund's daily raw return of each fund. N_t is the actual trading day at month t . $I_{[r_{t,d}<0]}$ is negative daily return dummy variable.

4.2 Construct Volatility managed strategy

After estimate realized volatility, Following Moreira and Muir (2017), I construct volatility-managed strategies by scaling each fund's monthly excess return by the inverse of its past realized volatility as equation (11)

$$R_{\sigma,i,t} = \frac{c}{\hat{\sigma}_{i,t-1}} R_{i,t} \quad (11)$$

where $R_{\sigma,i,t}$ is the monthly managed return. $R_{i,t}$ is fund excess return for fund i at month t . $\hat{\sigma}_{i,t-1}$ is realized volatility from the previous month estimate from equation (9) and (10). c is a scaling parameter that ensures the managed strategy maintains the same unconditional volatility as the unmanaged strategy. $\frac{c}{\hat{\sigma}_{i,t-1}}$ is the leverage that required investors to invest for volatility-managed position in month t .

The scaling parameter c , following Moreira and Muir (2017), is chosen to equalize the unconditional standard deviation between managed and unmanaged strategies, ensuring fair performance comparison. This is important because it allows direct measure of whether volatility-managed strategies improve risk-adjusted returns rather than reduce the overall risk. Moreover, since Sharpe ratios and alpha t-statistics are invariant to this scaling, the choice of c does not influence the performance measurement.

The construction of scaling parameter c that equalizes volatility between managed and unmanaged strategies follows a two-step process. The first step computes the initial volatility-managed strategy without scaling parameter c . This initial calculation is necessary to determine the standard deviation of the managed strategy before final adjustment:

$$R^*_{\sigma,i,t} = \frac{R_{i,t}}{\hat{\sigma}_{i,t-1}} \quad (12)$$

where $R_{\sigma,i,t}^*$ represents the initial managed return for fund i at time t . By dividing returns by volatility $\hat{\sigma}_{i,t-1}$, this initial managed return becomes a unitless measure since both the numerator and denominator are in percentage terms. From this initial managed return series, I calculate unitless standard deviation $\hat{\sigma}_{m,i}^*$.

The Second step, scaling parameter c can be computed by using standard deviations of unmanaged strategy divided by standard deviation of initial volatility managed return $\hat{\sigma}_{m,i}^*$.

$$c = \frac{\hat{\sigma}_{u,i}}{\hat{\sigma}_{m,i}^*} \quad (13)$$

where $\hat{\sigma}_{u,i}$ is the standard deviation of unmanaged returns for fund i in percentage terms and $\hat{\sigma}_{m,i}^*$ is the unitless standard deviation of initial managed returns for fund i . Because $\hat{\sigma}_{m,i}^*$ is unitless from equation (12), results in c being expressed in percentage terms. This construction ensures the final volatility-managed strategy maintains the same unconditional standard deviation as the unmanaged strategy by cancelling out the initial managed standard deviation $\hat{\sigma}_{m,i}^*$ when calculating the final volatility-managed strategy's standard deviation.

The effectiveness of this strategy can be illustrated through a practical example. Consider a fund with realized volatility $\hat{\sigma}_{i,t-1}$ of 5% and scaling parameter c of 4%. The strategy determines the investment position by calculating $\frac{c}{\hat{\sigma}_{i,t-1}}$, resulting in an 80% position (4%/5%). This position adjustment demonstrates two key mechanisms. First, the volatility timing ability reduces risk exposure when volatility is high. Second, the return timing mechanism helps prevent losses in subsequent periods. For instance, if the fund experiences a -10% return, the managed strategy will result in a -8% return (-10% \times 0.8), while an unmanaged position would incur the full -10% loss. This example illustrates how the strategy effectively captures benefits from both volatility persistence and the negative relationship between volatility and future returns without simply reducing the overall risk.

Repeat the calculation in equation (12) and (13) to obtain c_{Total} and c_{Down} for both total volatility-managed and downside volatility-managed strategies. After

obtaining the control parameters c_{Total} and c_{Down} , two volatility-managed strategies are constructed. The total volatility strategy scales unmanaged excess returns by past total realized volatility for each fund. Total volatility-managed strategy (Moreira and Muir, 2017):

$$R_{\sigma,t}^{\text{Total}} = \frac{c_{\text{Total}}}{\hat{\sigma}_{\text{Total},t-1}} R_t \quad (14)$$

where $R_{\sigma,t}^{\text{Total}}$ is the total volatility return at month t of each fund. c_{Total} is the control parameter for the total volatility. $\hat{\sigma}_{\text{Total},t-1}$ is the previous month's downside realized volatility from equation (9).

Downside volatility-managed strategy (Barroso and Maio, 2017):

$$R_{\sigma,t}^{\text{Down}} = \frac{c_{\text{Down}}}{\hat{\sigma}_{\text{Down},t-1}} R_t \quad (15)$$

where $R_{\sigma,t}^{\text{Down}}$ is the total volatility return at month t of each fund. c_{Down} is the control parameter for the total volatility. $\hat{\sigma}_{\text{Down},t-1}$ is the previous month's downside realized volatility from equation (10).

4.3 Examining fund risk-adjusted performance

To study risk-adjusted performance of volatility-managed strategies, I compute two risk-adjusted performance ratios for each strategy. The Sharpe ratio measures excess return per unit of total risk:

Sharpe ratio

$$\text{Sharp ratio} = \frac{E[R_i]}{\hat{\sigma}_i} \quad (16)$$

The Sortino ratio focuses on downside risk:

$$\text{Sortion ratio} = \frac{E[R_i]}{\hat{\sigma}_{\text{down},i}} \quad (17)$$

where $\hat{\sigma}_i$ represents total volatility and $\hat{\sigma}_{\text{down},i}$ captures downside volatility of fund i . $E[R_i]$ is expected excess return of fund i .

In term of risk-adjusted return ratios, the performance of volatility-managed strategies can be compared with unmanaged strategy. If Sharp ration and Sortino ration of volatility-managed is higher this indicate that investor can improve performance by using these strategies.

Importantly, as a goal of this study to explore the risk-adjusted performance of volatility-managed strategies, alpha is estimated by using Fama French 5-factor model. I estimate alpha fund by fund for each strategy.

Fama-French five-factor model (Fama and French, 2015):

$$R_{i,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t} \quad (18)$$

where $R_{i,t}$ is the monthly excess return of fund i . α_i is abnormal return of fund i , which represent fund risk adjusted performance. $\beta_{n,i}$ is the sensitivity of factor n of the model on fund i . $R_{m,t}$ is the total return from SET index at month t . $R_{f,t}$ is 1-month Thai T-bill rate at month t . SMB_t is the monthly return difference between equity portfolio small market capitalized and large market capitalized. HML_t is the monthly return difference between equity portfolio high book to market and low book to market. where RMW_t captures the profitability factor and CMA_t represents the investment factor.

The choice of the five-factor model is motivated by its demonstrated ability to explain volatility-related patterns in returns. Ang et al. (2006) document the model's effectiveness in capturing the volatility anomaly, while Jordan and Riley (2015) show that apparent fund performance differences often disappear when evaluated using this more comprehensive factor model. This suggests the model provides a robust framework for assessing whether volatility management generates genuine alpha.

To study risk-adjusted return performance, I focus on α_i in equation (19). If α_i is positive mean that the mutual fund better than the market. To evaluate the performance in difference strategies. I compare number of positive α_i , mean α_i the α_i

differences between unmanaged and managed strategy. A positive difference in alphas between managed and unmanaged strategies indicates that volatility-managed strategies enhance fund performance compared to the unmanaged approach.

Based on empirical evidence from developed and emerging markets (Wang et al., 2021; Zhang et al., 2024), this study hypothesizes that volatility-managed strategies enhance risk-adjusted returns for Thai mutual fund investors. I believe that volatility-managed strategies generate superior risk-adjusted returns compared to unmanaged strategies. Furthermore, downside volatility management is expected to yield greater performance improvements than total volatility management.

These analyses are repeated incorporating transaction costs. Following Moreira and Muir (2017), Three levels of transaction costs are considered including 3 basis points, 10 basis points, and 15 basis points. This allows examination of whether the benefits of volatility management persist after accounting for trading costs.

4.4 Comparison of performance of volatility-managed strategies across market conditions

To examine whether volatility-managed strategies perform differently across various market conditions, the sample period is divided into two distinct sub-periods based on market trends. Following the methodology in section 4.3, both total and downside volatility-managed strategies are examined across these periods to understand the conditions under which these strategies are effective.

The sub-periods are defined as follows. The bull market period from January 2005 to December 2014 represents a favorable market phase for Thai mutual funds. The bear market period from January 2015 to December 2024 represents a challenging market phase with different volatility-return dynamics.

This sub-period analysis investigates whether volatility-managed strategies are effective consistently across different market environments. The comparison examines how the underlying relationship between past volatility and future returns varies between bull and bear market conditions. By analyzing performance across these two distinct market environments, the study can determine whether these strategies provide

universal benefits or are conditional on the prevailing market trend and volatility-return dynamics.

4.5 Comparison of performance of volatility-managed strategies between actively managed and passively managed mutual funds

The effectiveness of volatility-managed strategies is analyzed between actively and passively managed mutual funds in the Thai market. Following the methodology in section 4.3, both total and downside volatility-managed strategies are examined by dividing the sample into two groups, actively managed funds and passively managed funds (index funds). This comparison allows examination of strategy performance across different fund management approaches.

The analysis between active and passive funds is particularly relevant as volatility management benefits may vary based on the underlying investment style. Active funds, which typically exhibit higher volatility due to discretionary trading and concentrated positions, may present greater opportunities for volatility management. Meanwhile, passive funds with their lower baseline volatility from tracking market indices might show different patterns in the effectiveness of these strategies. This comparative analysis provides insights into whether the benefits of volatility management are universal across fund management styles or more pronounced in certain fund types.

4.6 Examining volatility timing and return timing

Following Wang et al. (2021), I examine what drives the performance gains of volatility-managed strategies by testing both volatility timing and return timing effects.

For volatility timing, I analyze the relationship between funds' past volatility and current volatility:

$$\sigma_{i,t} = \alpha_i + \beta_{1,i}\sigma_{i,t-1} + \varepsilon_i \quad (19)$$

For return timing, I examine the relationship between funds' past volatility and current return:

$$r_{i,t} = \alpha_i + \beta_{1,i}\sigma_{i,t-1} + \varepsilon_i \quad (20)$$

where $\hat{\sigma}_{i,t}$ is the fund's realized volatility at month t and $\sigma_{i,t-1}$ is the lagged realized volatility. $r_{i,t}$ is the fund's return at month t .

The analysis of performance gains focuses on two key coefficients that characterize volatility dynamics. First, for volatility timing, coefficient $\beta_{1,i}$ in equation (20) captures the persistence of volatility. A positive $\beta_{1,i}$ indicates that current fund volatility follows the same direction as past volatility, supporting the effectiveness of volatility-managed strategies. This relationship enables investors to reduce exposure when recent volatility is high and increase positions when volatility is low, thereby optimizing risk exposure.

The persistence of volatility is one of the important facts of volatility literature. However, Wang et al. (2021) empirical result find that past volatility of all sample could predict future volatility. To hypothesize volatility timing, past volatility can predict the future volatility for both total and downside volatility. This predictability pattern suggests that scaling investment positions inversely to past volatility allows investors to effectively manage their exposure to future volatility risk.

For return timing, I focus on $\beta_{1,i}$ in equation (20). If the $\beta_{1,i}$ is negative, this indicate that the current return of each fund move opposite direction of the past volatility. Investors can increase their investment position when past volatility is low, which enhances investment returns, while reducing positions when past volatility is high helps avoid periods of low returns. Together with volatility timing effects, this pattern provides evidence for why volatility-managed strategies can improve performance.

The relationship between risk and return is a fundamental concept in finance, suggesting higher risk should be compensated with higher expected returns. However, Wang et al. (2021) find that past volatility and future returns have a negative relationship in mutual funds, indicating that high volatility periods are not compensated with proportionally higher returns. To hypothesize return timing, past volatility is expected to have a negative relationship with future returns, with downside volatility

exhibiting a stronger predictive pattern than total volatility. This pattern suggests that reducing investment positions during high volatility periods helps investors avoid times of potentially lower returns while increasing exposure during low volatility periods captures higher returns.

4.7 Examining Fund flow

To examine whether Thai mutual fund investors implement volatility-managed strategies in practice, the relationship between fund flows and past volatility is analyzed through three distinct volatility measures. Following standard methodology in mutual fund literature, the following regression is estimated:

$$\text{Flow}_{i,t} = \beta_{0,t} + \beta_{1,t}\sigma_{i,t-1} + \beta' \text{control} + \varepsilon_i \quad (23)$$

where $\text{Flow}_{i,t}$ represents the net percentage growth in fund i at month t , excluding growth from returns. The lagged volatility measure $\sigma_{i,t-1}$ is examined separately using total volatility, upside volatility, and downside volatility to provide comprehensive understanding of how investors respond to different types of risk. The regression includes several control variables known to affect fund flows: the log of fund age, the log of total net assets, lagged fund flow, annual fund excess returns during the past 12 months and the past 12-24 months, and the squared terms of these past returns. Each month's observations are analyzed separately, and the time-series averages of coefficient estimates are reported. Statistical significance is assessed using Fama-MacBeth methodology.

The analysis focuses on coefficient β_1 , which captures the relationship between fund flow and volatility. A negative β_1 indicates that investors reduce their positions in funds that recently experienced high volatility, suggesting awareness and implementation of volatility-managed strategies. Conversely, a positive or statistically insignificant β_1 would indicate that mutual fund investors are not actively implementing volatility timing in their investment decisions. By examining this relationship across different volatility measures, the analysis provides evidence on whether investors distinguish between and respond differently to total, upside, and downside volatility risks.

The theoretical framework suggests that sophisticated investors should reduce their fund investments when volatility is high and increase positions when volatility is low. Zhang et al. (2024) find in the Chinese market, where individual investors dominate, most investors do not actively engage in volatility timing, though institutional investors show some evidence of volatility-timing behavior. For Thai mutual fund investor, it is hypothesized that fund flows will show a negative relationship with past volatility, particularly with downside volatility, and this relationship will be more pronounced among sophisticated investors. However, given the significant retail investor presence in the Thai market, the overall flow-volatility relationship might be weaker compared to developed markets where institutional investors dominate.

5. Empirical result

5.1 Baseline Analysis

To evaluate the benefit of volatility-managed strategies, the volatility-managed strategies' risk-adjusted performance (α) is first examined using the Fama-French five-factor model. Three strategies are compared: unmanaged strategy, total volatility-managed strategy, and downside volatility-managed strategy across all funds, active funds, and passive funds separately. The risk-adjusted performance results from January 2005 to December 2024 are shown in Table 2.

The risk-adjusted performance results using the Fama-French five-factor model are presented in Table 3. The average monthly alpha for unmanaged funds is -0.09% (-1.08% annually), with 28.16% of funds achieving positive alphas, indicating that Thai mutual funds, on average, underperform the market. For the total volatility-managed strategy, the average alpha is -0.18% per month (-2.16% annually), with 34.66% of funds showing positive alphas. The downside volatility-managed strategy shows an average alpha of -0.12% per month (-1.44% annually), with 41.88% of funds having positive alphas.

Table 2: Volatility-Managed Fund Returns vs. Unmanaged Fund Returns All samples period, January 2005–December 2024

This table reports the risk-adjusted performance comparison between unmanaged strategy, total volatility-managed strategy, and downside volatility-managed strategy using the Fama-French five-factor model. The analysis is conducted through time-series regression for each fund over the entire sample period across Thai domestic equity mutual funds using the following equation for each strategy:

Unmanaged strategy:

$$R_{i,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

Total volatility managed:

$$R_{\text{total},i,t} = \alpha_{\text{Total},i} + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

Downside volatility managed:

$$R_{\text{down},i,t} = \alpha_{\text{Down},i} + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

The table presents results separately for all fund strategies, active funds, and passive funds. For each strategy, the table reports the average alpha (α_i), the percentage of funds with a positive alpha, and the cross-sectional percentiles of alpha estimates. The differences in alphas between managed returns and unmanaged returns are also reported to compare the strategies' effects. Alphas are expressed in decimal form representing monthly returns. Statistical significance is assessed using standard t-tests. The ** and * indicate statistical significance at the 1% and 5% levels, respectively. T-statistics are shown in parentheses.

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
FF5 α for all fund strategies					
α_i	-0.0009** (-7.47)	28.16%	-0.0034	-0.0008	0.0012
$\alpha_{\text{Total},i}$	-0.0018** (-9.54)	34.66%	-0.0062	-0.0015	0.0022
$\alpha_{\text{Down},i}$	-0.0012** (-4.23)	41.88%	-0.0075	-0.0013	0.0046
$\alpha_{\text{Total},i} - \alpha_i$	-0.0010** (-6.92)	36.82%	-0.0038	-0.0015	0.0022
$\alpha_{\text{Down},i} - \alpha_i$	-0.0003 (-1.19)	42.96%	-0.0047	-0.0008	0.0048
FF5 α for Active funds					
α_i	-0.0009** (-7.28)	29.20%	-0.0034	-0.0009	0.0012
$\alpha_{\text{Total},i}$	-0.0020** (-9.49)	33.60%	-0.0066	-0.0017	0.0022
$\alpha_{\text{Down},i}$	-0.0012** (-4.21)	41.60%	-0.0076	-0.0013	0.0046
$\alpha_{\text{Total},i} - \alpha_i$	-0.0010** (-7.02)	36.00%	-0.0039	-0.0015	0.0022
$\alpha_{\text{Down},i} - \alpha_i$	-0.0003 (-1.19)	42.80%	-0.0047	-0.0008	0.0048
FF5 α for Passive funds					
α_i	-0.0003** (-2.60)	18.52%	-0.001	-0.0004	0.0005
$\alpha_{\text{Total},i}$	-0.0007 (-1.59)	44.44%	-0.0038	-0.0007	0.0024
$\alpha_{\text{Down},i}$	-0.0005 (-0.65)	44.44%	-0.0039	-0.0018	0.0043
$\alpha_{\text{Total},i} - \alpha_i$	-0.0003 (-0.83)	44.44%	-0.0034	-0.0006	0.0026
$\alpha_{\text{Down},i} - \alpha_i$	-0.0001 (-0.18)	44.44%	-0.0044	-0.0013	0.0045

The alpha differences between managed and unmanaged strategies show that the total volatility-managed strategy underperforms the unmanaged strategy by -0.10% per month (-1.20% p.a.), which is statistically significant at the 1% level. Only 36.82%

of funds experience positive alpha differences. The downside volatility-managed strategy shows a smaller negative alpha difference of -0.03% per month (-0.36% p.a.), which is not statistically significant. However, 42.96% of funds show positive alpha differences, suggesting that nearly half of the funds benefit from downside volatility management. Moreover, active funds demonstrate similar patterns to the overall sample. The total volatility-managed strategy for active funds shows negative alpha differences of -0.10% monthly (-1.20% p.a.), while downside volatility management shows a non-significant negative alpha difference of -0.03% monthly (-0.36% p.a.). Passive funds show different behavior. While only 18.52% of unmanaged passive funds show positive alphas, 44.44% of both total and downside volatility-managed passive funds exhibit positive alphas. The alpha differences for passive funds are -0.03% monthly (-0.36% p.a.) for total volatility management and -0.01% monthly (-0.12% p.a.) for downside volatility management.

The evidence shows that volatility-managed strategies do not beat the market in the Thai mutual fund market during the full sample period. The negative alpha differences indicate that managed strategies underperform unmanaged strategies rather than providing the expected performance enhancement. Both active and passive funds demonstrate similar patterns of underperformance when using volatility-managed strategies during the full sample period. However, the fact that some funds still show positive alpha differences from unmanaged strategies suggests that volatility management effectiveness may depend on specific market conditions and time periods rather than being consistent across the entire sample period.

5.2 Sub-period Analysis

To examine whether volatility-managed strategies perform differently across various market conditions including bull markets, bear markets, and crisis periods, the sample period is divided into four sub-periods as shown in Table 3. The pre-2015 period (January 2005–December 2014) represents a bull market, while the post-2015 period (January 2015–December 2024) represents a bear market for Thai mutual funds.

Table 3: Volatility-Managed Fund Returns vs. Unmanaged Fund Returns, Sub-periods

This table reports the risk-adjusted performance comparison between unmanaged strategy, total volatility-managed strategy, and downside volatility-managed strategy across different market periods using the Fama-French five-factor model. The analysis is conducted through time-series regression for each fund over the entire sample period across Thai domestic equity mutual funds using the following equation for each strategy:

Unmanaged strategy:

$$R_{i,t} = \alpha_i + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

Total volatility managed:

$$R_{\text{Total},i,t} = \alpha_{\text{Total},i} + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

Downside volatility managed:

$$R_{\text{Down},i,t} = \alpha_{\text{Down},i} + \beta_{1,i}(R_{m,t} - R_{f,t}) + \beta_{2,i}(\text{SMB}_t) + \beta_{3,i}(\text{HML}_t) + \beta_{4,i}(\text{RMW}_t) + \beta_{5,i}(\text{CMA}_t) + \varepsilon_{i,t}$$

The table presents results separately for all fund strategies, active funds, and passive funds. For each strategy, the table reports the average alpha (α_i), the percentage of funds with a positive alpha, and the cross-sectional percentiles of alpha estimates. The differences in alphas between managed returns and unmanaged returns are also reported to compare the strategies' effects. Alphas are expressed in decimal form representing monthly returns. Panel A shows the bull market period (Pre-2015, January 2005–December 2014), Panel B shows the bear market period (Post-2015, January 2015–December 2024). Statistical significance is assessed using standard t-tests. ** and * indicate statistical significance at the 1% and 5% levels, respectively. T-statistics are shown in parentheses.

Panel A: Bull market period, January 2005–December 2014

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
FF5 α for all fund strategies					
α_i	-0.0010** (-4.31)	33.33%	-0.0036	-0.0005	0.0015
$\alpha_{\text{Total},i}$	0.0037** (9.49)	83.76%	-0.0043	0.0049	0.0076
$\alpha_{\text{Down},i}$	0.0076** (17.82)	89.74%	-0.0006	0.0092	0.0116
$\alpha_{\text{Total},i} - \alpha_i$	0.0047** (16.28)	93.16%	0.0016	0.0056	0.0070
$\alpha_{\text{Down},i} - \alpha_i$	0.0086** (23.23)	93.16%	0.0049	0.0098	0.0115
FF5 α for Active funds					
α_i	-0.0011** (-4.26)	31.43%	-0.0044	-0.0008	0.0017
$\alpha_{\text{Total},i}$	0.0035** (8.27)	81.90%	-0.0046	0.0049	0.0076
$\alpha_{\text{Down},i}$	0.0075** (15.94)	88.57%	-0.0021	0.0092	0.0122
$\alpha_{\text{Total},i} - \alpha_i$	0.0046** (14.60)	92.38%	0.0013	0.0056	0.0070
$\alpha_{\text{Down},i} - \alpha_i$	0.0086** (21.07)	92.38%	0.0046	0.0099	0.0115
FF5 α for Passive funds					
α_i	-0.0002 (-1.06)	50.00%	-0.0012	0.0000	0.0004
$\alpha_{\text{Total},i}$	0.0050** (11.38)	100.00%	0.0029	0.0051	0.0066
$\alpha_{\text{Down},i}$	0.0087** (14.96)	100.00%	0.0059	0.0096	0.0106
$\alpha_{\text{Total},i} - \alpha_i$	0.0052** (13.02)	100.00%	0.0030	0.0057	0.0066
$\alpha_{\text{Down},i} - \alpha_i$	0.0089** (14.79)	100.00%	0.0060	0.0095	0.0108

Panel B: Bear market period, January 2015–December 2024

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
FF5 α for all fund strategies					
α_i	-0.0010** (-8.53)	23.47%	-0.0034	-0.0011	0.0012
$\alpha_{Total,i}$	-0.0029** (-18.96)	7.22%	-0.0065	-0.0025	-0.0003
$\alpha_{Down,i}$	-0.0029** (-14.86)	17.33%	-0.0075	-0.0024	0.0011
$\alpha_{Total,i} - \alpha_i$	-0.0019** (-21.42)	5.05%	-0.0038	-0.0016	-0.0004
$\alpha_{Down,i} - \alpha_i$	-0.0018** (-13.00)	21.30%	-0.0047	-0.0017	0.0013
FF5 α for Active funds					
α_i	-0.0011** (-8.21)	24.40%	-0.0035	-0.0011	0.0013
$\alpha_{Total,i}$	-0.0030** (-18.23)	8.00%	-0.0066	-0.0027	-0.0002
$\alpha_{Down,i}$	-0.0029** (-13.85)	18.80%	-0.0078	-0.0025	0.0012
$\alpha_{Total,i} - \alpha_i$	-0.0019** (-20.97)	2.80%	-0.0040	-0.0017	-0.0004
$\alpha_{Down,i} - \alpha_i$	-0.0018** (-12.04)	21.60%	-0.0047	-0.0017	0.0015
FF5 α for Passive funds					
α_i	-0.0005** (-3.67)	14.81%	-0.0011	-0.0006	0.0002
$\alpha_{Total,i}$	-0.0018** (-7.51)	0.00%	-0.0038	-0.0017	-0.0005
$\alpha_{Down,i}$	-0.0024** (-7.27)	3.70%	-0.0039	-0.0023	-0.0005
$\alpha_{Total,i} - \alpha_i$	-0.0013** (-5.27)	25.93%	-0.0034	-0.0011	0.0001
$\alpha_{Down,i} - \alpha_i$	-0.0019** (-5.46)	18.52%	-0.0044	-0.0013	0.0001

The alpha differences across different periods show substantial variation, revealing that volatility-managed strategies benefit investors only during specific market periods. During Bull market period (Panel A), both total and downside volatility-managed strategies significantly outperform unmanaged strategies with positive alpha differences, all statistically significant at the 1% level. In the bull market period, total volatility management shows positive alpha differences of 0.47% monthly (5.64% p.a.) while downside volatility management achieves 0.86% monthly (10.32% p.a.) compared to the unmanaged buy-and-hold strategy. Downside volatility management provides larger benefits than total volatility management during these beneficial periods, with both active and passive funds benefiting and passive funds showing 100% positive alpha differences. However, during Bear market period (Panel B), volatility-managed strategies significantly underperform unmanaged strategies with negative alpha differences. The post-2015 period shows alpha differences of -0.19% monthly (-2.28% p.a.) for total volatility management and -0.18% monthly (-2.16% p.a.) for downside volatility management.

These sub-period results demonstrate that volatility-managed strategies do work effectively, but their performance depends on market conditions rather than being

universally effective. The sub-period analysis reveals that while the baseline analysis showed overall negative performance, the strategies perform well during bull market periods but fail during bear market conditions. This indicates that the effectiveness of volatility-managed strategies is conditional on the underlying market environment rather than the strategies being inherently ineffective.

These results demonstrate that volatility-managed strategies can be effective in the Thai market, but their success depends on specific market conditions. The strategies work well during bull market periods but underperform during bear market periods. This conditional effectiveness differs from the studies by Wang et al. (2021) and Zhang et al. (2024), who documented consistent positive performance for volatility-managed strategies in the U.S. and Chinese markets throughout their study periods, suggesting that market conditions significantly affect strategy effectiveness.

This period-dependent effectiveness suggests that volatility-managed strategies are not universally beneficial but depend on underlying market dynamics that vary across time. To address the second objective of this study, Chapter 5.5 will examine the return timing and volatility timing mechanisms to understand the sources of performance gains and explain why these strategies work in some periods but not others.

5.3 Sharpe Ratios and Sortino Ratios

The previous sections demonstrate that volatility-managed strategies outperform unmanaged strategies only during a specific period. For mean-variance utility-maximizing investors, the Sharpe ratio provides a more comprehensive measure of risk-adjusted performance (Cederburg et al., 2020). The Sharpe ratio and Sortino ratio results for the beneficial period is examined and presented in Table 4.

During the bull market period, volatility-managed strategies deliver substantially higher Sharpe ratios than unmanaged strategies. The average Sharpe ratio for unmanaged funds is 0.5279, while the total volatility-managed strategy achieves 0.7761, representing a 47% improvement. The downside volatility-managed strategy performs best with a Sharpe ratio of 0.9187, which is 74% higher than the unmanaged strategy. Active funds show improvements of 48% and 76% for total and downside

volatility management respectively, while passive funds demonstrate gains of 43% and 62%. The percentage of funds with positive Sharpe ratios remains high across all strategies, with downside volatility management showing the highest percentages.

Table 4: Sharpe Ratios and Sortino Ratios

This table reports the Sharpe ratios and Sortino ratios of three strategies: unmanaged strategy, total volatility-managed strategy, and downside volatility-managed strategy. The Sharpe ratio is calculated as $\frac{E[R_i]}{\hat{\sigma}_i}$ and the Sortino ratio is calculated as $\frac{E[R_i]}{\hat{\sigma}_{\text{down},i}}$. Panel A shows results for Bull market period (January 2005–December 2014). The table presents results for all funds, active funds, and passive funds for both Sharpe and Sortino ratios. For each strategy, the table reports the average ratio, the percentage of funds with a positive ratio, and the cross-sectional percentiles of ratio estimates. The Sharpe ratio measures excess return per unit of total risk, while the Sortino ratio measures excess return per unit of downside risk.

Panel A: Bull market period, January 2005–December 2014

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
Sharpe Ratio - All Funds					
Unmanaged	0.5279	94.87%	0.3071	0.5326	0.8813
Total Vol Managed	0.7761	95.73%	0.5523	0.8357	1.0726
Downside Vol Managed	0.9187	97.44%	0.6614	0.9344	1.2901
Sharpe Ratio - Active funds					
Unmanaged	0.5213	94.29%	0.2996	0.5326	0.8478
Total Vol Managed	0.7692	95.24%	0.3908	0.8357	1.0490
Downside Vol Managed	0.9154	97.14%	0.6131	0.9344	1.2992
Sharpe Ratio - Passive funds					
Unmanaged	0.5862	100.00%	0.4553	0.5268	0.8913
Total Vol Managed	0.8363	100.00%	0.6875	0.8206	1.0779
Downside Vol Managed	0.9481	100.00%	0.8131	0.9042	1.1744
Sortino Ratio - All Funds					
Unmanaged	0.7175	94.87%	0.4412	0.6896	1.2284
Total Vol Managed	1.2730	95.73%	0.7389	1.3206	1.7576
Downside Vol Managed	1.9262	97.44%	1.3200	1.8753	2.8261
Sortino Ratio - Active funds					
Unmanaged	0.7109	94.29%	0.4150	0.6954	1.1980
Total Vol Managed	1.2701	95.24%	0.5767	1.3327	1.7715
Downside Vol Managed	1.9472	97.14%	1.0672	1.8916	2.8861
Sortino Ratio - Passive funds					
Unmanaged	0.7751	100.00%	0.5540	0.6545	1.3181
Total Vol Managed	1.2977	100.00%	1.0194	1.2041	1.7078
Downside Vol Managed	1.7425	100.00%	1.4397	1.6874	2.1260

The Sortino ratio results show even stronger improvements during the bull market period. The unmanaged strategy achieves a Sortino ratio of 0.7175, while the total volatility-managed strategy reaches 1.2730, representing a 77% improvement. The

downside volatility-managed strategy delivers the highest Sortino ratio of 1.9262, which is 168% higher than the unmanaged strategy. Performance gains are consistent across fund management styles, with active funds achieving improvements of 79% and 174%, and passive funds experiencing gains of 67% and 125% for total and downside volatility management respectively.

The Sharpe ratio and Sortino ratio results confirm the effectiveness of volatility-managed strategies for both active and passive funds during the bull market periods. The substantial improvements in both ratios for each fund type demonstrate that volatility-managed strategies enhance returns rather than reduce risk, since these strategies are constructed to have the same unconditional standard deviation as unmanaged strategies through the scaling parameter. The consistent outperformance across both measures and fund management styles shows that volatility-managed strategies genuinely improve the return-generating process when market conditions are favorable, with both active and passive funds experiencing significant benefits from these approaches.

5.4 Transaction Costs Analysis

Volatility-managed strategies rebalance portfolios monthly, resulting in high turnover and non-zero transaction costs that may offset the gains from volatility scaling. Following Wang et al. (2021) and Zhang et al. (2024), the effect of transaction costs is evaluated and presented in Tables 5 and 6.

Table 5 shows that volatility-managed strategies require moderate trading activity during beneficial periods. In the bull market period (Panel A), average monthly weight changes are 0.37% for total volatility management and 0.48% for downside volatility management. Even after deducting trading fees at 45 basis points, the expected return differences remain positive at 0.26% for total volatility management and 0.44% for downside volatility management. At 45 basis points, the expected returns are still substantial, indicating that significantly higher trading costs would be required to eliminate the performance benefits entirely.

Table 5: The Effect of Transaction Costs on the Performance of Volatility-managed Strategies

This table examines the impact of transaction costs on volatility-managed strategies during selected periods when these strategies performed well. Panel A shows results for Bull market period. For each strategy, the table reports the average absolute change in monthly weights ($|\Delta\omega|$), expected return differences compared to unmanaged strategies, and performance after accounting for transaction costs ranging from 3 to 45 basis points. Results are shown separately for all funds, active funds, and passive funds using both total volatility-managed and downside volatility-managed strategies.

Panel A: Bull market period - The Effect of Transaction Costs

Strategy	$ \Delta\omega $	E[R]	Difference with Unmanaged	Difference after trading cost				
				3 bps	10 bps	15 bps	25 bps	45 bps
Total volatility managed strategy								
All samples	0.37%	1.29%	0.42%	0.41%	0.39%	0.37%	0.33%	0.26%
Active	0.37%	1.28%	0.42%	0.41%	0.38%	0.36%	0.33%	0.25%
Passive	0.36%	1.41%	0.44%	0.42%	0.40%	0.38%	0.34%	0.27%
Downside volatility managed strategy								
All samples	0.48%	1.53%	0.66%	0.64%	0.61%	0.58%	0.54%	0.44%
Active	0.48%	1.52%	0.66%	0.65%	0.61%	0.59%	0.54%	0.44%
Passive	0.46%	1.60%	0.62%	0.61%	0.58%	0.55%	0.51%	0.42%

Table 6: Volatility-managed vs. Unmanaged Performance After Transaction Cost

This table reports the net performance differences between volatility-managed and unmanaged strategies after accounting for transaction costs. Panel A presents results for the bull market period (January 2005–December 2014) with low transaction costs ranging from 3 to 45 basis points. Panel B presents results for the same period with high transaction costs ranging from 100 to 200 basis points. The table shows alpha differences between managed and unmanaged strategies net of transaction costs for both total volatility-managed and downside volatility-managed strategies. Results are presented separately for all funds, active funds, and passive funds. ** and * indicate statistical significance at the 1% and 5% levels, respectively. T-statistics are shown in parentheses.

Panel A: Low transaction costs, Bull market period (January 2005–December 2014)

		$\alpha_{total,i} - \alpha_i$			$\alpha_{down,i} - \alpha_i$		
		All	Active	Passive	All	Active	Passive
Low trading costs	15 bps	0.0041**	0.0040**	0.0046**	0.0079**	0.0079**	0.0082**
		(14.09)	(12.59)	(11.81)	(20.84)	(18.87)	(13.77)
	25 bps	0.0037**	0.0037**	0.0043**	0.0074**	0.0074**	0.0078**
		(12.64)	(11.28)	(10.97)	(19.25)	(17.42)	(13.08)
	45 bps	0.0030**	0.0029**	0.0035**	0.0065**	0.0065**	0.0068**
		(9.81)	(8.72)	(9.23)	(16.16)	(14.58)	(11.66)

Panel B: High transaction costs, Bull market period (January 2005–December 2014)

		$\alpha_{total,i} - \alpha_i$			$\alpha_{down,i} - \alpha_i$		
		All	Active	Passive	All	Active	Passive
Hight trading costs	100 bps	0.0010** (2.84)	0.0009* (2.42)	0.0015** (4.00)	0.0039** (8.51)	0.0038** (7.62)	0.0043** (7.55)
	125 bps	0.0000 (0.14)	-0.0000 (-0.01)	0.0005 (1.48)	0.0027** (5.55)	0.0026** (4.93)	0.0031** (5.58)
	150 bps	-0.0009* (-2.28)	-0.0009* (-2.18)	-0.0004 (-1.10)	0.0015** (2.91)	0.0014* (2.53)	0.0019** (3.55)
	200 bps	0.0027** (-6.32)	0.0028** (-5.80)	0.0023** (-6.25)	-0.0009 (-1.51)	-0.0009 (-1.45)	-0.0004 (-0.71)

Table 6 demonstrates that volatility-managed strategies remain robust against substantial transaction costs during the bull market period. Even at 45 basis points, alpha differences are 0.30% monthly for total volatility management and 0.65% monthly for downside volatility management, both statistically significant at the 1% level. The analysis of higher trading costs reveals distinct break-even points for each strategy. Total volatility management maintains positive performance until approximately 100 basis points, while downside volatility management demonstrates superior cost tolerance, remaining profitable until around 150 basis points. These findings are consistent with Wang et al. (2021) and Zhang et al. (2024), though both the U.S. and Chinese markets typically feature lower trading costs than the Thai market. The results conclusively demonstrate that Thai mutual fund investors can benefit from total volatility-managed strategies when trading costs remain below 100 basis points and from downside volatility-managed strategies when costs stay below 150 basis points, regardless of mutual fund styles.

5.5 Source of Performance Gains

To address the second objective of this study and understand why volatility-managed strategies work in some periods but not others, the sources of performance gains are examined through volatility timing and return timing analysis. Both past total volatility and downside volatility are used as predictor variables. Fund-by-fund regressions are conducted, and the results are presented in Table 7.

Table 7: Source of Performance Gains Analysis

This table reports the results of volatility timing and return timing analysis to identify the sources of performance gains from volatility-managed strategies. The analysis examines whether past volatility can predict current volatility (volatility timing) and whether past volatility can predict current returns (return timing) using these equations:

Return timing:

$$\text{Total volatility measure: } R_{i,t} = \alpha_i + \beta_1 \sigma_{i,t-1}^{\text{total}} + \varepsilon_i$$

$$\text{Downside volatility measure: } R_{i,t} = \alpha_i + \beta_1 \sigma_{i,t-1}^{\text{down}} + \varepsilon_i$$

Volatility timing

$$\text{Total volatility measure: } \sigma_{i,t}^{\text{total}} = \alpha_i + \beta_1 \sigma_{i,t-1}^{\text{total}} + \varepsilon_i$$

$$\text{Downside volatility measure: } \sigma_{i,t}^{\text{down}} = \alpha_i + \beta_1 \sigma_{i,t-1}^{\text{down}} + \varepsilon_i$$

Panel A to E show results for different time periods: Full sample, Bull market, Bear market periods. For each regression, the table reports the mean coefficient, the percentage of funds with statistically significant coefficients at the 10% level, and the cross-sectional percentiles of coefficient estimates. Statistical significance is assessed using Newey-West standard errors. T-statistics are calculated from the sample to determine significance levels. ** and * indicate statistical significance at the 1% and 5% levels, respectively. T-statistics are shown in parentheses.

Panel A: Full sample, January 2005 - December 2024 - The source of gains

Variable	Mean	Percentage Significant	10th Percentile	Median	90th Percentile
β_1 Return timing					
$\sigma_{i,t-1}^{\text{total}}$	0.0405** (16.54)	0.3321	-0.0007	0.0372	0.0876
$\sigma_{i,t-1}^{\text{down}}$	0.0329** (13.51)	0.1264	-0.0078	0.0337	0.0800
β_1 Volatility timing					
$\sigma_{i,t-1}^{\text{total}}$	0.4453** (40.10)	0.8412	0.1285	0.5191	0.5776
$\sigma_{i,t-1}^{\text{down}}$	0.2860** (22.71)	0.7581	-0.0532	0.3868	0.4370

Panel B: Bull market, January 2005 - December 2014 - The source of gains

Variable	Mean	Percentage Significant	10th Percentile	Median	90th Percentile
β_1 Return timing					
$\sigma_{i,t-1}^{\text{total}}$	-0.0255** (-9.67)	40.17%	-0.0462	-0.0294	-0.0109
$\sigma_{i,t-1}^{\text{down}}$	-0.0375** (-12.41)	63.25%	-0.0639	-0.0394	-0.0233
β_1 Volatility timing					
$\sigma_{i,t-1}^{\text{total}}$	0.4484** (62.61)	94.87%	0.3789	0.4533	0.5351
$\sigma_{i,t-1}^{\text{down}}$	0.3755** (52.27)	93.16%	0.3042	0.3550	0.4851

Panel C: Bear market, January 2015 - December 2024 - The source of gains

Variable	Mean	Percentage Significant	10th Percentile	Median	90th Percentile
β_1 Return timing					
$\sigma_{i,t-1}^{\text{total}}$	0.0521** (26.25)	41.52%	0.0294	0.0425	0.0876
$\sigma_{i,t-1}^{\text{down}}$	0.0474** (24.97)	13.36%	0.0268	0.0421	0.0800
β_1 Volatility timing					
$\sigma_{i,t-1}^{\text{total}}$	0.4412** (40.36)	84.12%	0.1285	0.5141	0.5681
$\sigma_{i,t-1}^{\text{down}}$	0.2811** (22.68)	75.81%	-0.0532	0.3735	0.4299

The results of testing the relationship between lagged volatility and current returns reveal critical differences between periods. During Bull market period (pre-2015), the mean β are significantly negative at the 1% level for both total and downside volatility, with mean β of -0.0255 for total volatility and -0.0375 for downside volatility. During the bear market period (post-2015), the relationship reverses to positive with mean β of 0.0521 for total volatility and 0.0474 for downside volatility. This means that during the bull market, high volatility in past month is followed by low returns in the next month, which is the opposite of bear market periods.

The results show that volatility timing works consistently across all periods as presented in Panel A to Panel C. The mean β_1 for predicting current volatility are significantly positive at the 1% level across all periods, ranging from 0.44 to 0.45 for total volatility and 0.28 to 0.38 for downside volatility. The percentage of funds with significantly positive β_1 remains high, ranging from 84.12% to 94.87% for total volatility and 78.81% to 93.16% for downside volatility across different periods, allowing volatility-managed strategies to predict future volatility effectively.

The findings show that return timing changes between different market conditions, while volatility timing remains consistent throughout sample periods. During bull markets, past volatility negatively predicts future returns because low volatility aligns with steady upward trends, and volatility spikes often indicate that a sharp correction may follow. This allows strategies to reduce exposure in time and benefit from falling prices. During bear markets, this relationship reverses to positive, which works against the strategies. In bear markets, volatility spikes are often followed by continued gains driven by investor momentum, while periods of low volatility reflect pessimism and ongoing selling. Volatility timing works across all market conditions

because past volatility consistently predicts future volatility. This explains why volatility-managed strategies work well during bull markets but underperform during bear markets where positive return timing works against the strategies.

These findings align with Wang et al. (2021) and Zhang et al. (2024) regarding volatility timing but show important differences in return timing patterns. Wang et al. (2021) found that past volatility consistently predicted future volatility for their sample funds, and past volatility negatively predicted future returns for most of their sample funds. Zhang et al. (2024) documented that both volatility timing and return timing contribute to superior performance. However, unlike these studies where the negative volatility-return relationship remained consistent throughout their sample periods, the Thai market shows that return timing changes dramatically between bull and bear market conditions while volatility timing stays consistent. This explains why volatility-managed strategies work only during specific market conditions with negative return timing rather than being universally effective across all periods.

5.6 Fund Flows and Volatility

To address the third objective of this study and examine whether Thai mutual fund investors implement volatility-managed strategies in practice, the relationship between fund flows and past volatility is analyzed. Fund flows reflect investor behavior and indicate whether investors recognize and act on volatility signals when making investment decisions. The results are presented in Table 8.

The results conclusively demonstrate that Thai mutual fund investors respond negatively to past volatility across all volatility measures as presented in Table 8. In Model 1, lagged total volatility produces a coefficient of -0.1055, statistically significant at the 1% level, confirming that investors systematically reduce their fund investments when total volatility has been high. Model 2 reveals that lagged upside volatility generates a coefficient of -0.1795, significant at the 1% level. Model 3 establishes that lagged downside volatility exhibits a coefficient of -0.0985, also significant at the 1% level. All three models consistently demonstrate that Thai investors decrease their fund investments following periods of high volatility, regardless of whether the volatility stems from positive or negative price movements.

Table 8: Impact of Fund Volatility on Fund Flows, January 2005–December 2024

This table reports pooled ordinary least squares (OLS) regression results examining the relationship between fund flows and lagged volatility measures. The results of the regression model use different volatility measures, where model 1 uses lagged total volatility, model 2 uses lagged upside volatility, and model 3 uses lagged downside volatility as follows:

$$\text{Model 1: Flow}_{i,t} = \beta_0 + \beta_1 \sigma_{i,t-1}^{\text{Total}} + \beta_2 \text{Log(Age)}_{i,t} + \beta_3 \text{Log(TNA)}_{i,t} + \beta_4 \text{Flow}_{i,t-1} + \beta_5 R_{t-1} + \beta_6 R_{t-1}^2 + \beta_7 R_{t-2} + \beta_8 R_{t-2}^2 + \varepsilon_{i,t}$$

$$\text{Model 2: Flow}_{i,t} = \beta_0 + \beta_1 \sigma_{i,t-1}^{\text{Up}} + \beta_2 \text{Log(Age)}_{i,t} + \beta_3 \text{Log(TNA)}_{i,t} + \beta_4 \text{Flow}_{i,t-1} + \beta_5 R_{t-1} + \beta_6 R_{t-1}^2 + \beta_7 R_{t-2} + \beta_8 R_{t-2}^2 + \varepsilon_{i,t}$$

$$\text{Model 3: Flow}_{i,t} = \beta_0 + \beta_1 \sigma_{i,t-1}^{\text{Down}} + \beta_2 \text{Log(Age)}_{i,t} + \beta_3 \text{Log(TNA)}_{i,t} + \beta_4 \text{Flow}_{i,t-1} + \beta_5 R_{t-1} + \beta_6 R_{t-1}^2 + \beta_7 R_{t-2} + \beta_8 R_{t-2}^2 + \varepsilon_{i,t}$$

** and * indicate statistical significance at the 1% and 5% levels, respectively. T-statistics are shown in parentheses.

Variable	Model (1)	(2)	(3)
β_0	1.9612 (1.78)	2.0738 (1.86)	1.7668 (1.62)
$\sigma_{t-1}^{\text{Total}}$	-0.1055** (-6.74)		
σ_{t-1}^{Up}		-0.1795** (-6.79)	
$\sigma_{t-1}^{\text{Down}}$			-0.0985** (-5.78)
Log(Age)	-0.3116** (-4.11)	-0.3163** (-4.16)	-0.3060** (-4.04)
Log(TNA)	-0.0638 (-1.31)	-0.0654 (-1.35)	-0.0619 (-1.28)
Flow _{t-1}	0.0005 (0.02)	0.0005 (0.02)	0.0005 (0.02)
R _{t-1}	-0.0212** (-8.45)	-0.0206** (-8.22)	-0.0204** (-8.35)
R _{t-1} ²	0.0003** (3.56)	0.0004** (3.84)	0.0003** (3.00)
R _{t-2}	0.0337** (10.47)	0.0351** (10.71)	0.0331** (10.32)
R _{t-2} ²	-0.0002** (-3.40)	-0.0002** (-3.71)	-0.0002** (-3.32)
# of observations	22,820	22,820	22,820

The negative relationships between fund flows and all volatility measures suggest that Thai mutual fund investors are aware of volatility timing benefits and actively implement these strategies in their investment decisions. Investors withdraw money from funds that have recently experienced high volatility and presumably invest more when volatility is low. This behavior aligns with the principles of volatility-managed strategies. However, as demonstrated in previous sections, the effectiveness of this volatility timing behavior depends on the underlying market conditions and whether high volatility is followed by low returns or high returns.

The evidence indicates that Thai mutual fund investors recognize the potential risks associated with high volatility and adjust their investment behavior accordingly. The negative flow-volatility relationship suggests that investors understand that high volatility periods may signal poor future performance and act to reduce their exposure.

These findings align with Wang et al. (2021), who found evidence of a negative relationship between fund flows and past fund volatility in the U.S. market, suggesting that U.S. fund investors are aware of the benefit of volatility management. However, the results contrast with Zhang et al. (2024), who found no obvious relationship between fund flows and past total volatility in the Chinese market. Zhang et al. (2024) noted that individual investors in China, who dominate the market, use simple buy-and-hold strategies and do not engage in volatility timing, while only institutional investors showed awareness of volatility timing benefits. The Thai market results suggest that Thai investors demonstrate awareness of volatility timing principles similar to U.S. investors.

6. Conclusion

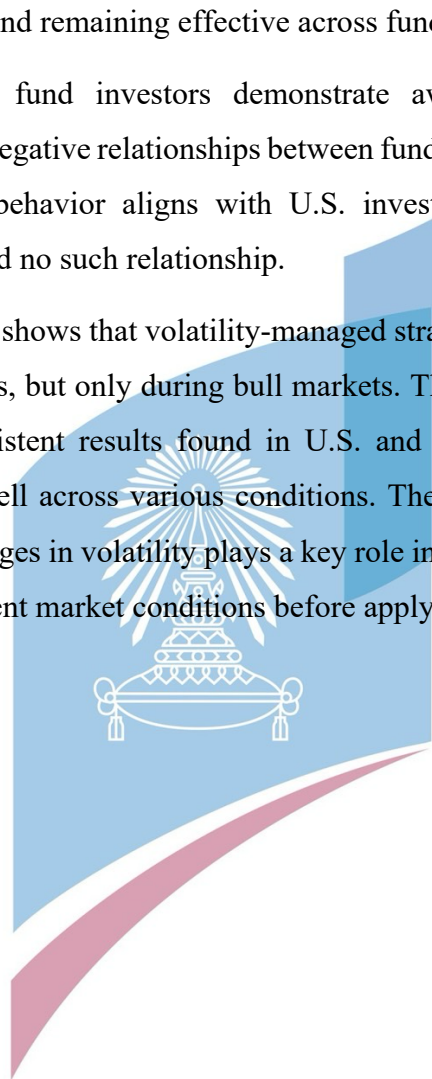
This study examines whether volatility-managed strategies can benefit Thai mutual fund investors from January 2005 to December 2024, using Fama-French five-factor alphas, Sharpe ratios, and Sortino ratios as performance measures.

Volatility-managed strategies are effective in the Thai mutual fund market during specific market conditions when high volatility is followed by weaker returns, particularly in bull markets. This effectiveness stems from different investor behavior patterns across market cycles. In bull markets, volatility spikes signal upcoming

corrections, allowing strategies to reduce exposure before downturns. In bear markets, however, volatility spikes are followed by continued gains driven by investor momentum, while low volatility periods reflect ongoing selling pressure. These behavioral differences explain why strategies outperform in bull markets but underperform in bear markets. During favorable market conditions, volatility-managed strategies improve risk-adjusted performance, with downside volatility strategy improving the most and remaining effective across fund investment styles.

Thai mutual fund investors demonstrate awareness of volatility timing principles, showing negative relationships between fund flows and past volatility across all measures. This behavior aligns with U.S. investors but differs from Chinese investors who showed no such relationship.

The evidence shows that volatility-managed strategies can be effective for Thai mutual fund investors, but only during bull markets. This limited effectiveness differs from the more consistent results found in U.S. and Chinese markets, where these strategies perform well across various conditions. The findings suggest that how the market reacts to changes in volatility plays a key role in determining success. Investors should consider current market conditions before applying these strategies.



REFERENCES

- Barroso, P., Detzel, A.L. (2021). Do Limits to Arbitrage Explain the Benefits of Volatility-Managed Portfolios? *Journal of Financial Economics* 140, 774-767.
- Barroso, P., Maio, P. (2018). Managing the Risk of the "Betting-Against-Beta" Anomaly: Does it Pay to Bet Against Beta? Unpublished working paper. University of New South Wales.
- Barroso, P., Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116, 111–120.
- Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1), 57–82.
- Cederburg, S., O'Doherty, M.S., Wang, F., Yan, X. (2020). On the performance of volatility-managed portfolios. *Journal of Financial Economics*, 138, 95-117.
- Charoenwong, B., Nettayanun, S., and Saengchote, K. (2021). Digesting anomalies: A q-factor approach for the Thai market. *Pacific-Basin Finance Journal*, 69.
- Eisdorfer, A., Misirli, U. (2020). Distressed stocks in distressed times. *Management Science*, 66, 2452-2473.
- Fama, E., French, K.R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.
- Fama, E. F., French, K.R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.
- Fleming, J., Kirby, C., Ostdiek, B. (2001). The economic value of volatility timing. *Journal of Finance*, 56, 329–352.
- Fleming, J., Kirby, C., Ostdiek, B. (2003). The economic value of volatility timing using “realized” volatility. *Journal of Financial Economics*, 67, 473–509.
- Jensen, M. C. (1967). The performance of mutual funds in the period 1945-1964. *Journal of Finance*, 23(2), 389-416.
- Moreira, A., Muir, T. (2017). Volatility-managed portfolios. *Journal of Finance*, 72, 1611–1644.
- Patton, A. J., Sheppard, K. (2015). Good volatility, bad volatility: signed jumps and the persistence of volatility. *The Review of Economics and Statistics*, 97, 673-697.
- Sirri, E. R., Tufano, P. (1998). Costly search and mutual fund flows. *Journal of Finance*, 53, 1589–1622.
- Wang, F., Yan, X.S., Zheng, L. (2021). Should mutual fund investors time volatility? *Financial Analysts Journal*, 77, 30-42.

Zhang, X., Zheng, Y., Lien, D., Yu, X. (2024). Can mutual fund investors benefit from volatility managing? Evidence from China. *Pacific-Basin Finance Journal*, 83, 102228.



AUTHOR BIOGRAPHY

NAME	Nattapong Shutimayotingul
DATE OF BIRTH	9 December 1994
PLACE OF BIRTH	Bangkok, Thailand
INSTITUTIONS ATTENDED	Bachelor of Engineering (Civil Engineering - Water Resources), Kasetsart University (2013-2017)
HOME ADDRESS	255 Ladprao, Chokchai 4 Soi 9, Wang Thonglang, Bangkok 10310
PUBLICATION	Click or tap here to enter text.
AWARD RECEIVED	

