The Impact of Thailand Volatility Index on Stock Returns Across Different Capitalization: A Comparative Analysis of Pre-Pandemic and COVID-19 eras

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Abstract

This research investigates the influence of the Thailand Volatility Index (TVIX) on the returns of stocks within the FTSE SET Index Series, which categorizes Thai companies by market capitalization (large, mid, and small). The analysis employs a simple linear regression model using daily data from May 6, 2014 to December 27, 2023. This regression analysis leverages stationary time series data. The results show a negative impact of TVIX on returns, with this effect being stronger for smaller companies and during the post-pandemic period. Lagged TVIX terms were also significant, suggesting the persistence of volatility's influence. Further analysis using a multiple regression model explored the impact of additional factors, for instance, Covid-19 case numbers in Thailand, Geopolitical Risk (GPR), and Return on Gold and Oil Prices. The pre-pandemic analysis for large-cap stocks indicated the importance of these variables. Interestingly, the inclusion of COVID-19 cases in the post-pandemic model did not significantly influence returns. These findings suggest that TVIX remains a key factor for investors, particularly for smaller capitalization stocks, while the direct impact of COVID-19 cases might be less prominent on returns within the FTSE SET Index.

Keywords: FTSE SET Index, Market Capitalization, Thailand Volatility Index, Volatility Impact

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ผลกระทบของดัชนีความผันผวนของตลาดหลักทรัพย์ไทย (TVIX) ต่อผลตอบแทนของหุ้นตามมูลค่าตลาด: การวิเคราะห์เปรียบเทียบระหว่างยุคก่อนและยุคโควิด-19

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บทคัดย่อ

บทความนี้ศึกษาความสัมพันธ์ระหว่างดัชนีความผันผวนของตลาดหลักทรัพย์ไทย (TVIX) กับผลตอบแทนของดัชนี FTSE SET แยกตามขนาดของมูลค่าตามราคาตลาด ทั้ง Large Cap, SET Mid Cap และ SET Small Cap ซึ่งเป็นตัวแทนผลตอบแทนของหุ้นไทยในกลุ่มขนาดตลาดที่แตกต่างกัน การวิเคราะห์ใช้แบบจำลองการถดถอยเส้นตรงแบบง่าย โดยใช้ข้อมูลรายวันตั้งแต่วันที่ 6 พฤษภาคม 2557 ถึงวันที่ 27 ธันวาคม 2566 การวิเคราะห์การถดถอยดำเนินการกับข้อมูลที่มีลักษณะนิ่ง (Stationary Data) ผลการวิจัยแสดงให้เห็นว่า TVIX มีผลกระทบเชิงลบต่อผลตอบแทนของหุ้นไทย โดยผลกระทบนี้จะรุนแรงขึ้น ในกรณีที่เป็นบริษัทขนาดเล็ก และอยู่ในช่วงหลังการแพร่ระบาดของโรคโควิด-19 นอกจากนี้ ผลของ TVIX ในอดีต ยังมีความสำคัญ ซึ่งบ่งชี้ถึงอิทธิพลที่คงอยู่ของความผันผวน การวิเคราะห์เพิ่มเติมโดยใช้แบบจำลองการถดถอยพหุคูณ ศึกษาผลกระทบของปัจจัยภายนอกเพิ่มเติม เช่น จำนวนผู้ติดเชื้อโควิด-19 ในประเทศไทย ความเสี่ยงทางภูมิรัฐศาสตร์ (GPR) และผลตอบแทนจากราคาทองคำและราคาน้ำมัน การวิเคราะห์ในกรณีก่อนเกิดการแพร่ระบาดของหุ้นขนาดใหญ่ชี้ให้เห็นถึงความสำคัญของตัวแปรเหล่านี้ ประเด็นที่น่าสนใจคือ ตัวแปรจำนวนผู้ติดเชื้อโควิด-19 ในแบบจำลองกรณีที่เป็นช่วงหลังการแพร่ระบาด พบว่าไม่มีผลกระทบต่อผลตอบแทนของหุ้นไทยอย่างมีนัยสำคัญ ดังนั้นผลการวิจัยเหล่านี้ชี้ให้เห็นว่า TVIX ยังคงเป็นปัจจัยสำคัญสำหรับนักลงทุน โดยเฉพาะหุ้นขนาดเล็ก ในขณะที่ผลกระทบโดยตรงต่อผลตอบแทนภายในดัชนี FTSE SET ของจำนวนผู้ติดเชื้อโควิด-19 อาจมีน้อยกว่า

คำสำคัญ: ดัชนีความผันผวนของประเทศไทย, ดัชนีตลาดหลักทรัพย์แห่งประเทศไทย, ผลกระทบจากความผันผวน, มูลค่าหลักทรัพย์ตามราคาตลาด

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1. Introduction

The absence of an official volatility index based on the Stock Exchange of Thailand (SET) poses the notable gap in the local financial landscape, unlike the well-established CBOE VIX in the United States derived from S&P 500 options prices, which serves as a crucial tool for investors in assessing market sentiment and option pricing. While prior research studying about the computation of Thailand's Volatility Index (Arayathakul et al., 2022) attempted to construct a model to compute Thailand's volatility index or TVIX, revealing a negative correlation with the SET50 index, further empirical testing is imperative to ascertain the efficacy of TVIX as a robust risk management instrument for Thai investors.

Consequently, this study seeks to fill this gap by focusing on the key objectives which includes exploring how the Thailand Volatility Index (TVIX) affects the Thai stock market, particularly examining how sensitive various market capitalization segments (large, mid, and small cap) are to fluctuations in TVIX, and investigating variations in TVIX under distinct economic circumstances, such as the COVID-19 crisis. While existing literature provides insights into popular methods or models for these research objectives, a comprehensive examination is required, particularly in the investigation of the relationship between TVIX and the Thai stock market. This study examines the explanatory power of the Thailand volatility index (TVIX) on the FTSE SET Index Series. It employs a quantitative approach, utilizing time-series data spanning from May 6th, 2014, to December 27th, 2023. This period encompasses both pre-pandemic and COVID-19 eras corresponding to the objective of comparative analysis before and during COVID-19 crisis. The research begins by gathering secondary data of all included factors which are as follows.

This study delves into the relationship between the Thai stock market and TVIX as a sentiment indicator. To achieve this, the research focuses on three core objectives. First, it is to examine the application of TVIX as a proxy of "Market Sentiment Indicator" within the context of the Thai stock market. Second, the study investigates how changes in TVIX, affect the returns of the FTSE SET Index Series. This series represents the performance of small-cap, mid-cap, and large-cap stocks in Thailand, allowing for analysis across different market capitalizations. Finally, the research compares the impact of TVIX on the various stock categories before and during the COVID-19 crisis. By analyzing these different time periods, the study aims to identify any potential shifts in the relationship between TVIX and stock returns brought about by the pandemic.

By analyzing the TVIX's influence across these objectives, the research investigates the significance of the TVIX, a market volatility index, in understanding the Thai stock market. First, it aims to assess how effectively the computed TVIX functions as a proxy for market sentiment, specifically by evaluating its relative influence on stock market fluctuations. Second, the research provides valuable insights into the varying levels of TVIX among distinct series within the FTSE SET Index, each representing the different capitalization of Thai stocks. Thirdly, the research seeks to enhance comprehension of the behavioral patterns of the Thai stock market during periods of different volatility due to the change in economic conditions. Finally, the research will explore the influence of additional risk factors, beyond the TVIX, that are assumed to be associated with stock returns and TVIX fluctuations themselves. By examining these four aspects, this research will offer a comprehensive analysis of how the TVIX can be utilized to gain a deeper understanding of the Thai stock market's dynamics.

Understanding the impact of market sentiment, proxied by the TVIX, on the returns of Thai stocks across different market capitalizations, is the core focus. The FTSE SET Index Series along with its Large, Mid, and Small Cap sub-indices will be used to represent these stock categories. The study will focus solely on data from the Stock Exchange of Thailand (SET), CEIC, and authorized sources. Data analysis will be conducted in two phases: Python will be used for development and initial analysis of the TVIX alongside all relevant data preparation. Subsequently, EViews software will be employed to explore relationships and patterns between the FTSE indices, TVIX, and other included factors. To quantify these relationships, the research will utilize both simple and multiple regression models. The simple regression model will examine the link between the FTSE indices and TVIX, while the multiple regression model will incorporate additional factors such as the Geopolitical Risk (GPR) Index, COVID-19 cases in Thailand, and returns on gold and oil prices. Finally, the analysis will be conducted across two time periods: pre-COVID (May 6, 2014 to December 30, 2019) and during the COVID-19 crisis (January 1, 2020 to December 27, 2023).

2. Literature review

Development of Thailand's Volatility Index (TVIX)

In the preceding study, "Numerical Methods for Calculating Thailand's Volatility Index," conducted by Arayathakul, Sittitam, and Tangrungruangchai (2022), was made to formulate a model for the computation of Thailand's volatility index, denoted as TVIX. The research fundamentally describes options pricing models, specifically employing the Black-Scholes model, and integrates numerical methods such as the Newton and Raphson methods for calculating implied volatility (IV). Additionally, the research includes the procedure for determining Thailand's volatility index (TVIX).

Black-Scholes Model

The Black-Scholes model marked a significant milestone in the theoretical understanding and the estimation of option pricing. Notably, this model holds appeal due to its provision of a closed-form solution for pricing European-style options. What sets the Black-Scholes model apart is its reliance on the observed market variables, except for the volatility measure. This characteristic contributed to the expansion of options markets by providing efficient pricing technology.

Originally designed for non-dividend paying securities in the context of European-style options, the Black-Scholes model can be adapted to price various types of options. This adaptability enhances its practical utility in different financial scenarios. The Black-Scholes formulas for pricing European Calls (C) and Puts (P) in the case of non-dividend-paying stocks are presented below, reflecting the enduring relevance and versatility of this influential model.

$$C = SN(d_1) - Ke^{-rt}N(d_2)$$

$$P = Ke^{-rt}N(-d_2) - SN(-d_1)$$

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

C: call option price

P: put option price

S: spot price of underlying asset

K: strike price of option

r: risk-free interest rate

t: time to expiration of the option content

σ: volatility of the underlying asset

N: a normal distribution

Newton-Raphson Method

Option traders frequently employ the Newton-Raphson method to iteratively estimate implied volatility. This approach entails an initial guess of implied volatility, with subsequent iterations refining the estimate based on the option price, the market price of the option, and the Vega, which is the derivative of the option price with respect to volatility, all in terms of the initial guess.

The formula for the Newton-Raphson method in the context of implied volatility estimation can be expressed as follows;

$$\sigma_{i+1} = \sigma_i - \frac{C(\sigma_i) - C_m}{\frac{\delta_C}{\delta_{\sigma_i}}}$$

σ_i: the initial guess for the implied volatility if (i=0)

$C(\sigma_i)$: the option price derived from the initial guess.

C_m: the market price of the option

$\frac{\delta_C}{\delta_{\sigma_i}}$: obviously the Vega in terms of the initial guess

Once specific criteria are met, the ultimate implied volatility for the option is determined. Initial estimates can be obtained from various sources, including alternative formulas, experience, or random selection. The Newton-Raphson approach is known for its speed, and when initial predictions are accurate, it significantly enhances the efficiency of the model. Consequently, many option traders prefer this method. It's essential to note that this technique relies on the availability of Vega's value, which can be computed analytically for European-style options.

The old VXO

The VXO, a preceding volatility index, approximates the volatility swap rate under specific assumptions. It is defined based on the 1-month Black-Scholes at-the-money implied volatility, incorporating an upward bias attributed to an inaccurate trading-day conversion. The

CBOE favored the VIX over VXO, citing the new VIX's more widely recognized and robust economic interpretation.

As outlined in the research paper titled "Volatility Index for the Thai Stock Market (TVIX)" by The Market Risk Department of Asia Plus Securities Co. Ltd (2017), the calculation of the VIX for trading options in Thailand, represented by TVIX, is suggested to adopt the VXO methodology. The study posits that VXO aligns more effectively with the current data of option market circumstances, particularly in situations where at-the-money options are actively traded over their lifespan.

Steps of TVIX Calculation

In the computation process, it utilized the steps and formulas derived from Carr and Wu (2006), which has significantly contributed to the understanding of the steps to calculate TVIX. The explanation of the calculation steps is presented below.

1. Inspect the spot price of SET50 index at the specified period.
2. Find the 2 nearest maturities of that specified period then assign the first and the second nearest maturities as T1 and T2, respectively. Note that if the time to the nearest maturity is less than eight calendar days, the next two nearest maturities are used instead.

Repeat step 3 to 8 twice for maturity T1 and T2

3. Select 4 near-the-money options which are two call options and two put options of the two strike prices that straddle the spot level.
4. Calculate the IV for each option.
5. Average the two implied volatilities of call options and put options that have the same strike price.
6. Linearly interpolation the average implied volatility between two strike prices, and assign the result as $\boldsymbol{AMTV(t, T_i)}$
7. Calculate NT using the formula below.

$$\boldsymbol{NT = NC - 2 \times int\left(\frac{NC}{7}\right)}$$

$\boldsymbol{NC}$: number of actual days of the time to reach maturity
$\boldsymbol{NT}$: number of trading days between time t and the option expiry date T

8. Calculate □□(□, □□) using the formula below.

$$\boldsymbol{TV(t, T_i) = AMTV(t, T_i)\frac{\sqrt{NC}}{\sqrt{NT}}}$$

$TV(t,T_i)$: trading-day volatility

9. Calculate TVIX from the VXO formula below.

$$VXO_t = TV(t,T_1)\frac{NT_2 - 22}{NT_2 - NT_1} + TV(t,T_2)\frac{22 - NT_2}{NT_2 - NT_1}$$

VXO: interpolated trading-day volatility at 22 trading days based on the two trading-day volatilities at the two nearest maturities $TV(t,T_1)$ and $TV(t,T_2)$.

The Figure 1 explores the potential negative relationship between the SET50 Index and the TVIX, similar to the observed behavior between the VIX (the US Volatility Index) and the S&P 500 Index (US Stock Market). The VIX is known as a "fear gauge" because it typically rises during periods of market uncertainty or economic instability. This increased fear leads investors to sell stocks and seek safer assets, causing the S&P 500 to decline. According to the line chart in this figure, it obviously illustrates that the rising TVIX (indicating higher volatility) might correspond with a decrease in the SET50 index. The line chart included likely visually depicts the historical trends of both indexes to support this investigation. While the pattern mirrors that of the VIX and the S&P 500 Index, with TVIX rising during periods of market instability, particularly during the COVID-19 pandemic, an issue with the initial computation of TVIX caused it to erroneously drop to zero on some occasions before the COVID-19 period.

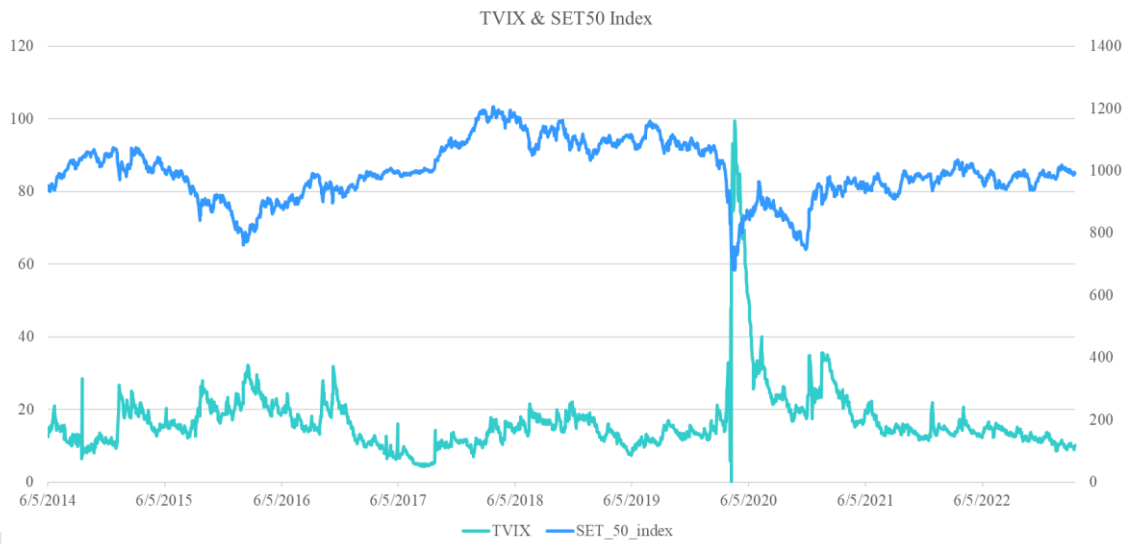

Figure 1: Visualization of computed TVIX (Arayathakul et al., 2022) compared to SET50 Index during the time period from May 2014 to February 2023.

Explanatory Variable

FTSE SET Index

The FTSE SET Index Series is a product of the partnership between the Stock Exchange of Thailand and FTSE Group, a prominent global index expert. This innovative set of benchmarks is created to assess the Thai capital market's performance, providing transparent and investible standards. These indices serve as a foundation for creating appealing index-linked products, catering to the interests of both local and international investors. The FTSE SET Index Series includes various segmented indices designed to meet diverse investment needs.

The FTSE SET Index Series categorizes Thai companies listed on the SET Main Board based on market capitalization.

1. Large Cap (FSTHL): Top 30 companies, calculated intra-second.
2. Mid Cap (FHTHM): Companies between 90th and top 30th percentile, calculated every 60 seconds.
3. Small Cap (FSTHS): Companies between 98th and 90th percentile, calculated every 60 seconds.
4. All-Share (FSTHA): All companies within the top 98th percentile, calculated every 60 seconds.
5. Mid/Small Cap (FSTHMS): Combination of Mid and Small Cap companies, calculated every 60 seconds.
6. Fledgling (FSTHF): Remaining 2% of smallest companies, calculated every 60 seconds.

Note: "Intra-second basis" denotes calculations taking place within each second for the FTSE SET Large Cap Index.

Geopolitical Risk (GPR) Index

A new study by Caldara and Iacoviello (2022) tracks geopolitical tension through newspaper articles since 1900. Their "Geopolitical Risk (GPR) index" shows spikes during major historical events like wars and 9/11. The research suggests that high geopolitical risk is linked to lower investments, falling stock prices, and fewer jobs. It also suggests a greater chance of economic crises and heightened risks for the global economy.

The GPR index is differentiated into the Recent GPR Index, starting in 1985 with data from 10 newspapers, and the Historical Index, originating in 1900 with data from 3 newspapers. Country-specific GPR indexes are also created for 44 countries, employing automated text-search results of electronic newspaper archives, according to Figure 2 which illustrates the calculated Recent GPR Index of Thailand. The computation of the indexes assesses the monthly share of relevant articles mentioning the country or its major cities, providing a U.S. perspective on the risks associated with each country.

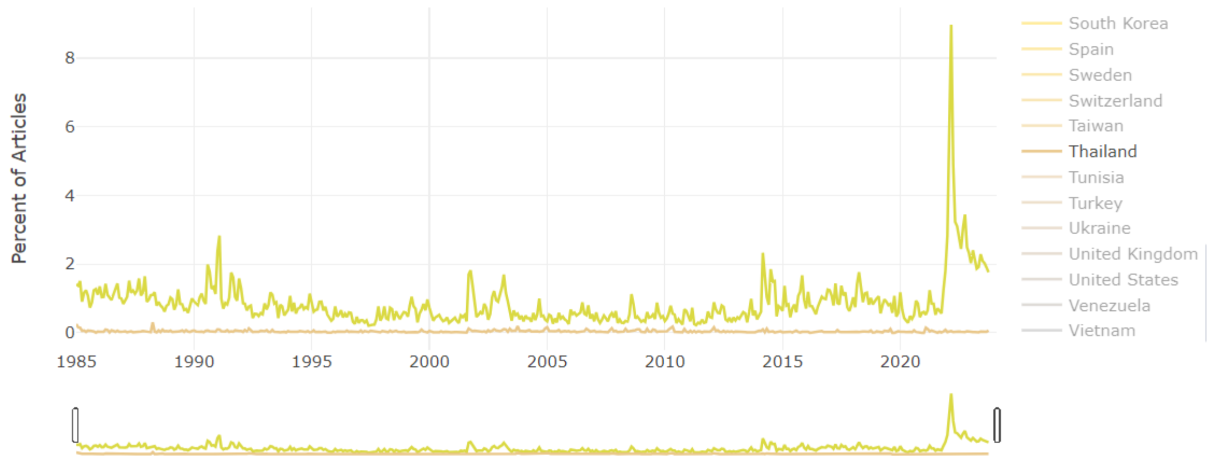

Figure 2: The Charts of historical Country-Specific GPR Indexes of Thailand expressed as a percentage of articles, from 1985 to the present day.

Relationship Investigation

Simple Linear Regression

Simple linear regression constitutes a statistical methodology employed to model the association between a single independent variable, often referred to as a predictor, and a dependent variable, also known as a response variable. This technique accomplishes this by fitting a linear equation to the observed data points. The equation below represents the fundamental form of a simple linear regression model:

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

Y : the dependent variable
X : the independent variable
β_0: the y-intercept
β_1: the slope of the line
ε : the error term

This model aims to determine the optimal values for coefficients (β_0 and β_1) within the linear model. These coefficients minimize the sum of squared errors between the observed dependent variable values and the values predicted by the model. The method of least squares is commonly employed to achieve this optimization.

Simple Linear Regression is a foundational technique in statistics and is widely employed in various fields for analyzing and modeling relationships between two variables (Thakolsri et al., 2016). As an example, this method was employed to investigate the influence of changes in the implied volatility index on the subsequent return on the underlying stock index within the Thai stock market. It serves as a basis for more complex regression analyses, such as multiple linear regression, which involve multiple independent variables.

Multiple Linear Regression

Multiple linear regression, often called MLR, is a statistical method used to see how multiple factors (independent variables) affect one outcome (dependent variable). This model is a more complex version of regular linear regression, which only looks at one factor at a time. MLR helps to understand how all these factors working together influence the focused outcome.

In simpler terms, MLR helps us explore how multiple factors simultaneously contribute to a single outcome. It's a powerful tool for various fields, including finance (predicting stock prices), economics (analyzing market trends), and the social sciences (examining the impact of multiple factors on social phenomena).

The core of MLR lies in the linear equation that represents the relationship between the variables. This equation takes the following general form:

$$\boldsymbol{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon}$$

Y: Dependent variable (the outcome we want to predict)
X_1 to X_n: Independent variables (the factors influencing the outcome)
β_0: Intercept (the value of Y when all independent variables are zero)
β_1 to β_n: Regression coefficients (represent the strength and direction of the influence of each independent variable on Y)
ε: Error term (accounts for the unexplained variance in the data)

The main aim of MLR is to find the best straight line that explains how the independent variables affect the dependent variable in a given dataset. For example, Thakolsri et al. (2016) used MLR to develop an equation that examines the separate effects of positive returns, negative returns, and past changes in an implied volatility index.

3. Data and Methodology

This study examines the explanatory power of the Thailand volatility index (TVIX) on the FTSE SET Index Series. It employs a quantitative approach, utilizing time-series data spanning from May 6, 2014, to December 27, 2023. This period encompasses both pre-pandemic and COVID-19 eras corresponding to the objective of comparative analysis before and during COVID-19 crisis. The research begins by gathering secondary data of all included factors according to Table 1.

This investigation into daily TVIXt data utilizes Python to compute the TVIX value in accordance with the methodology outlined in the research article (Arayathakul et al., 2022). Notably, the implemented Python code has been refined to effectively handle the potential presence of missing values or zero TVIX values arising from the computational process. Upon investigation, this error was traced to missing or unreported option price data on specific days, as provided by the TFEX (Thailand Futures Exchange). The initial computation did not account for such missing data, causing TVIX to incorrectly reach zero. To address this, the Python code for computing TVIX was improved to handle missing or incomplete data more effectively. The revised computation now ensures that TVIX never drops to zero due to data unavailability, and as a result, the error has been eliminated from the analysis.

This study takes daily data from the Investing website which encompasses three FTSE SET Index Series: FTSE SET Large Cap (FSTHL), FTSE SET Mid Cap (FSTHM), and FTSE SET Small Cap (FSTHS), denoted as R_FTSEserie, t to represent the first difference of the logarithm of each FTSE SET Index Series as the returns of small-cap, mid-cap, and large-cap Thai stocks. To investigate the influence of various factors on the FTSE SET Index Series, the model incorporates additional exogenous variables sourced from the CEIC database which the data were monthly recorded. These variables include: COVID19t, representing the number of confirmed COVID-19 cases in Thailand; GPRt, capturing Thailand's Geopolitical Risk Index as a percentage of articles; and GOLDt and OILt, representing the first difference of the logarithm of both price as the returns on gold and oil prices, respectively. The results obtained from analyzing the impact of these exogenous variables will be compared to the impact of TVIX.

Table 1: Definition of Variables and Source of Data

Variable	Definition	Source
$TVIX_t$	Thailand Volatility Index	"Numerical Methods for Calculating Thailand's Volatility Index", by Arayathakul, Sittitam, and Tangrungruangchai (2022), calculated using a python language program.
$R\_FTSE_{serie,t}$	Returns on FTSE SET Index of three series (Large, Mid, and Small)	Returns were calculated from 1st Differenced of ln of the FTSE SET Index of all series exported from www.investing.com
$COVID19_t$	Percent change of the confirmed COVID-19 case number	Percent change was calculated from the 1st Difference of the ln of COVID-19 Confirmed Case Number in Thailand exported from CEIC database
GPR_t	Thailand's Geopolitical Risk Index as Percent of Articles	CEIC database
$GOLD_t$	Gold Returns	Returns were calculated from 1st Difference of ln of Gold Bullion Selling Price exported from CEIC database
OIL_t	Oil Returns	Returns were calculated from 1st Difference of ln of Brent Crude Oil Spot Price exported from CEIC database

Once all relevant data has been gathered, it undergoes a comprehensive preparation process to ensure its suitability for model estimation. This involves utilizing Python programming to harmonize the data, ensuring temporal consistency by aligning data points within a common timeframe. Additionally, missing values or zero data points are meticulously addressed.

The initial step of the study involves conducting a Unit Root test to examine the stationarity of the data employed in the analysis. This is achieved using the Augmented Dickey-Fuller Test (ADF). The ADF test determines whether a time series exhibits a unit root, which implies a non-stationary nature and the presence of a random walk.

Due to the study's objective of evaluating TVIX's impact on Thai stock market returns, the collected data exhibits varying frequencies. TVIX and three FTSE SET Index Series are daily data, while other exogenous variables are monthly. To align with the study's objectives, data frequency conversion from daily to monthly is necessary. This involves averaging the daily values of each variable to obtain monthly data. To facilitate efficient data transformation, EViews software is employed. Once the data was appropriately prepared, then it is analyzed in EViews software to explore the relationship between TVIX and the FTSE SET Index Series, incorporating the exogenous variables.

Furthermore, the study divides the evaluation period into two distinct phases: pre-COVID-19 (May 6, 2014 - December 30, 2019) and post-COVID-19 (January 1, 2020 - December 27, 2023). This segmentation enables a comprehensive assessment of TVIX's influence on Thai stock returns under different market conditions

In this section, the econometric methodology is outlined to examine the relationship between political uncertainty and the Thai stock market. To investigate how TVIX influences the Thai stock market, the simple regression model with stationary series of data in the first-differenced form is used for estimation. This section includes daily data of FTSE all three series and TVIX. Hence, the following model is estimated:

$$R\_FTSE_{serie,t} = C_0 + C_1(\Delta TVIX_t) + e_t \tag{1}$$

where $R\_FTSE_{serie,t}$ is the dependent variable representing the return on a specific FTSE SET Index series; large, mid, or small, at time t. C1 is the coefficient of the independent variable $\Delta TVIX_t$ indicating the expected change in the return on the FTSE SET Index series for every unit change in the difference of TVIX.

$$R\_FTSE_{serie,t} = C_0 + C_1(\Delta TVIX_t) + C_2(\Delta TVIX_{t-1}) + C_3(\Delta TVIX_{t-2}) + C_3(\Delta TVIX_{t-3}) + e_t \tag{2}$$

The Equation (2) represents a modified version of the linear regression model used to analyze the relationship between change in TVIX and returns on the FTSE SET Index series (Large, Mid, and Small Cap). It investigates not only how the current change in TVIX affects returns, but also how the change in the three previous days; $\Delta TVIX_{t-1}$, $\Delta TVIX_{t-2}$, and $\Delta TVIX_{t-3}$, might influence them. This allows for a more comprehensive analysis by considering the potential persistence of volatility's impact on the stock market.

To broaden the study's scope and investigate the impact of additional exogenous variables, a multiple regression model was employed. This model aimed to assess whether these variables could better explain or influence the changes in FTSE SET Index returns (Large, Mid, and Small Cap series) compared to TVIX alone. Accordingly, the study adopted a stepwise approach, gradually incorporating monthly exogenous variables into the model one at a time. This process allowed for the observation of the resulting changes in the coefficients of TVIX and the newly introduced variables. The objective was to identify the model that provided the most comprehensive and optimal fit for analysis. Lastly, the findings revealed that the most effective and comprehensive model included all the exogenous variables. This model is represented by the following equation:

Pre-COVID-19 (May 2014 - December 2019):

$$R\_FTSE_{serie,t} = C_0 + C_1(\Delta TVIX_t) + C_2(\Delta GPR_t) + C_3(GOLD_t) + C_4(OIL_t) + e_t \tag{3}$$

Post-COVID-19 (January 2020 - December 2023):

$$R\_FTSE_{serie,t} = C_0 + C_1(\Delta TVIX_t) + C_2(\Delta GPR_t) + C_3(GOLD_t) + C_4(OIL_t) + C_5(COVID19_t) + e_t \tag{4}$$

The Equation (3) is further refined by segmenting the data into pre-COVID-19 (May 2014 to December 2019) and post-COVID-19 (January 2020 to December 2023) periods. This allows for a more nuanced analysis by potentially capturing how the impact of various factors might differ across these distinct economic environments. However, the core structure remains similar which $R\_FTSE_{serie,t}$ is returns on the FTSE SET Index series (Large, Mid, or Small Cap) at time t. C_1 is the coefficient of $\Delta TVIX_t$ together with C_2, C_3, C_4 as coefficients of exogenous variables; ΔGPR_t, $GOLD_t$ and OIL_t. In Equation (4), the post-COVID-19 equation introduces an additional term that is $C_5(COVID19_t)$, the coefficient of a new exogenous variable capturing the impact of the COVID-19 pandemic. It allows the model to account for the potential influence of the pandemic on the returns of the FTSE SET Index series. By estimating the coefficient C_5, the study can investigate if and how the COVID-19 pandemic affected the relationship between the traditional factors ($\Delta TVIX_t$, ΔGPR_t, $GOLD_t$, OIL_t) and the returns ($R\_FTSE_{serie,t}$).

This study proposes several hypotheses regarding the influence of TVIX on Thai stock returns. The first hypothesis is that, from Equation (1), it is expected that the change in TVIX will have a negative impact on the returns of all FTSE SET Index series (large, mid, and small cap). Similarly, in Equation (2), the second hypothesis is that the lagged change in TVIX ($\Delta TVIX_{t-1}$) from the previous day is also hypothesized to exhibit a negative relationship with current returns. For the third hypothesis, even when additional exogenous variables are incorporated as shown in Equation (3) and (4), the impact of TVIX on returns across all series is expected to remain significant. The fourth hypothesis from Equation (4) is among the exogenous variables, the introduction of COVID-19 cases ($COVID19_t$) in the post-COVID-19 equation is specifically hypothesized to influence the returns. For the last hypothesis, the study proposes that TVIX will have a stronger explanatory power for the returns of smaller capitalization (small cap) stocks compared to mid and large cap stocks within the FTSE SET Index because when the TVIX, which reflects market volatility expectations, increases, investors might be more likely to pull out of riskier assets like small-cap stocks, leading to a more pronounced negative impact on their returns compared to mid and large cap stocks.

4. Empirical Results

The stationarity of the employed variables was rigorously evaluated using the Augmented Dickey-Fuller (ADF) test, as shown in Table 2. To ensure that the variables were suitable for regression analysis, transformations were applied to make all variables stationary. Specifically, the first logarithmic difference was applied to all variables except the Geopolitical Risk Index (GPR), which was transformed using the first difference. Since the GPR reflects percentages, by using the first difference, the analysis remains straightforward and interpretable. This ensures that each variable is stationary and ready for further analysis.

Although the Thailand Volatility Index (TVIX) was found to be stationary at its level, the first logarithmic difference was applied in the regression analysis. This transformation was chosen for several reasons. First, it allows us to interpret the results in terms of percentage changes, which is more intuitive and meaningful in financial contexts. Second, it helps linearize the relationships between variables and reduce potential heteroscedasticity, improving the model's robustness. Finally, this ensures consistency with other financial variables, such as stock returns, which are commonly expressed as logarithmic differences.

As shown in Table 2, the null hypothesis of a unit root is rejected for all transformed variables at the 1% significance level, confirming their stationarity. These results ensure the robustness of the following regression analysis.

Table 2: Unit root test statistics of the returns on FTSE SET Index of all three series, Thailand volatility index and exogenous variables.

R_FTSE$_{Large}$	**R_FTSE$_{Mid}$**	**R_FTSE$_{Small}$**	**TVIX**	**COVID19**	**GPR**	**GOLD**	**OIL**
-12.0895*** (0.0000)	-11.5146*** (0.0000)	-12.7245*** (0.0000)	-5.3395*** (0.0000)	-5.4861*** (0.0000)	-8.4590*** (0.0000)	-8.2552*** (0.0000)	-8.2423*** (0.0000)

Note: The reported statistics are the daily TVIX, returns based on FTSE SET Index and the monthly exogenous variables. In the table, asterisks (*) are used to indicate statistical significance; ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are p-values.

To examine the presence of autocorrelation in the residuals and to determine the appropriate lag structure, a correlogram analysis was performed using EViews. This method provided a visual inspection of autocorrelation patterns through the autocorrelation function (ACF) and partial autocorrelation function (PACF) for the residuals. Based on the results of the correlogram, specific lag terms were identified and subsequently included in the regression models to account for any autocorrelation observed. The correlogram analysis guided the selection of different lag terms for the full period and the sub-periods (pre-COVID and post-COVID), reflecting distinct autocorrelation patterns within each time frame. This approach allowed for an accurate representation of the underlying dynamics within each period, enhancing the model's explanatory power.

The correlogram results revealed autocorrelation in some of the models across the three regression analysis periods: full sample (May 6, 2014, to December 27, 2023), pre-COVID-19 (May 6, 2014, to December 30, 2019), and post-COVID-19 (January 1, 2020, to December 27, 2023). To address this issue and ensure the validity of analysis in each period, lagged terms of the dependent variables were introduced into the relevant equations as seen in the following estimation results. While this process resulted in different lag selections for the full period and the sub-periods (pre-COVID and post-COVID), these variations reflect distinct autocorrelation patterns observed in each period. Given the structural shifts in the market, particularly around the COVID-19 pandemic, it was necessary to apply different lag structures to capture the true underlying dynamics of the data in each sub-period. The decision to use period-specific lags ensures that the models accurately represent the changing market environment. While different lags were used, consistent estimation techniques were applied across all models, allowing for meaningful comparisons between the full period and the sub-periods without compromising the reliability of the results.

The regression analysis, presented in Table 3, confirms a negative and statistically significant (at the 1% level) relationship between changes in TVIX and returns across all FTSE SET Index series (large, mid, and small cap) for the full sample period (May 6, 2014, to

December 27, 2023). This validates our hypothesis that increased volatility, as reflected by TVIX, leads to lower returns for Thai stocks. Interestingly, this negative impact is amplified for smaller companies. The coefficient estimates for the change in TVIX are most negative for small-cap stocks, followed by mid-cap and then large-cap stocks, indicating a greater susceptibility of smaller companies to volatility fluctuations.

Table 3: The effects of TVIX on Returns of FTSE SET Index series

Equations	**May 6, 2014 to December 27, 2023**	**May 6, 2014 to December 30, 2019**	**January 1, 2020 to December 27, 2023**
Panel A: $R\_FTSE_{Large,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Large,\, t\text{-}lag}) + C_{tvix}(\Delta TVIX_{\ t}) + e_t$			
Intercept	0.0000 (0.9080)	5.50E-05 (0.8048)	-0.0002 (0.7261)
$R\_FTSE_{Large,\, t-1}$	-0.0366 (0.0012)	-	-0.0655 (0.0008)
$R\_FTSE_{Large,\, t-2}$	0.0585 (0.0000)	-	0.0936 (0.0000)
$R\_FTSE_{Large,\, t-5}$	-	-	0.0772 (0.0008)
$R\_FTSE_{Large,\, t-6}$	-	-	-0.1278 (0.0000)
$R\_FTSE_{Large,\, t-9}$	-	-	0.1170 (0.0000)
$R\_FTSE_{Large,\, t-10}$	0.0431 (0.0012)	-	-0.1047 (0.0000)
$R\_FTSE_{Large,\, t-11}$	-0.0918 (0.0000)	-	-
$\Delta TVIX_{\ t}$	-0.0171*** (0.0000)	-0.0059*** (0.0078)	-0.0545*** (0.0000)
Adj. R^2	0.0426	0.0044	0.1479
Panel B: $R\_FTSE_{Mid,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Mid,\, t\text{-}lag}) + C_{tvix}(\Delta TVIX_{\ t}) + e_t$			
Intercept	0.0000 (0.9694)	0.0001 (0.6317)	-0.0002 (0.7023)
$R\_FTSE_{Mid,\, t-1}$	-	0.0744 (0.0026)	-
$R\_FTSE_{Mid,\, t-5}$	0.0536 (0.0000)	-	0.0812 (0.0000)
$R\_FTSE_{Mid,\, t-6}$	-	-	-0.0821 (0.0000)
$R\_FTSE_{Mid,\, t-8}$	-0.0697 (0.0000)	-	-

Equations	May 6, 2014 to December 27, 2023	May 6, 2014 to December 30, 2019	January 1, 2020 to December 27, 2023
$R\_FTSE_{Mid,\ t-11}$	0.0521 (0.0002)	-	-
$\Delta TVIX_t$	-0.0226*** (0.0000)	-0.0082*** (0.0000)	-0.0697*** (0.0000)
Adj. R^2	0.0625	0.0160	0.1818
Panel C: $R\_FTSE_{Small,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Small,\ t-lag}) + C_1(\Delta TVIX_t) + e_t$			
Intercept	0.0000 (0.9444)	-0.0002 (0.5901)	0.0003 (0.5353)
$R\_FTSE_{Small,\ t-1}$	0.0952 (0.0000)	0.1075 (0.0000)	0.1163 (0.0000)
$R\_FTSE_{Small,\ t-2}$	0.0454 (0.0002)	-	-
$R\_FTSE_{Small,\ t-4}$	0.0402 (0.0037)	-	-
$R\_FTSE_{Small,\ t-5}$	0.0394 (0.0170)	-	-
$R\_FTSE_{Small,\ t-6}$	-0.0590 (0.0000)	-	-0.0859 (0.0000)
$\Delta TVIX_t$	-0.0271*** (0.0000)	-0.012*** (0.0000)	-0.0787*** (0.0000)
Adj. R^2	0.0751	0.0318	0.1965

Note: The reported statistics are the daily TVIX and returns based on FTSE SET Index. In the table, asterisks (*) are used to indicate statistical significance; ***, ** and * denote significance at the **1%**, **5%**, and **10%** levels, respectively. The numbers in parentheses are p-values.

Further analysis reveals a difference in the magnitude of this effect between pre- and post-COVID-19 eras. While TVIX remains a significant negative factor for returns in both periods, the coefficient estimates become more negative in the post-COVID era for all market capitalizations. This suggests that volatility has a stronger negative impact on stock returns following the COVID-19 pandemic.

It's noteworthy that the intercept term in the regression model is very close to zero across all periods. This implies that when all other factors influencing returns are zero, the average return for each market capitalization category is negligible.

The analysis in Table 4 incorporates lagged TVIX terms to explore the influence of past volatility on returns. For the full sample, the coefficient of the change in current TVIX is negative and statistically significant at the 1% level for all capitalization sizes. This confirms the negative relationship between current volatility and returns. Interestingly, the impact of past volatility ($\Delta TVIX_{t.1}$, $\Delta TVIX_{t.2}$, *and* $\Delta TVIX_{t.3}$) weakens as we move back in time. The coefficients for lagged terms are statistically significant at the 1% level for $\Delta TVIX_{t.1}$ in for all capitalization sizes. However, the coefficients for $\Delta TVIX_{t-2}$ and $\Delta TVIX_{t-3}$ are not significant for any capitalization size. This suggests that the influence of past volatility diminishes beyond the previous period (t-1) for the full sample.

In the pre-COVID-19 period, the coefficients associated with lagged TVIX; $\Delta TVIX_{t-1}$, $\Delta TVIX_{t-2}$, *and* $\Delta TVIX_{t-3}$, were not statistically significant for any FTSE SET Index series. This suggests that contemporaneous changes in current TVIX ($\Delta TVIX_t$) exerted the strongest impact on returns during this period.

On the other hand, the post-COVID-19 period reveals a more distinct relationship. While the change in current TVIX (□TVIXt) remains significant and negatively associated with returns across all series, some lagged terms become statistically significant. For large-cap stocks, only the coefficient of the change in TVIX of the last period (□TVIXt-1) is significant at the level of 1% and exhibits a negative relationship, but its magnitude is smaller than the current TVIX impact. For mid-cap stocks, the change of TVIX, both at time t-2 and t-3 (□TVIXt-2, □TVIXt-3), have significant negative coefficients at 1% and 10% level, respectively, with the change in TVIX at time t-2 (□TVIXt-2) having a larger impact than time t-3 (□TVIXt-3). Finally, small-cap stocks show significant coefficients for the change in TVIX of the last period (□TVIXt-1) at 5% level and the change in TVIX at time t-2 (□TVIXt-2) at 1% level, with stronger negative effect than TVIX in the last period but both of them are smaller than the impact of the change in current TVIX.

Table 4: The effects of TVIX and past TVIX on Returns of FTSE SET Index series

Equations	**May 6, 2014 to December 27, 2023**	**May 6, 2014 to December 30, 2019**	**January 1, 2020 to December 27, 2023**
Panel A: $R\_FTSE_{Large,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Large,\ t\text{-}lag}) + C_{tvix,0}(\Delta TVIX_{\ t}) + \sum^{N=3} C_{tvix,n}(\Delta TVIX_{\ t\text{-}n}) + e_t$			
Intercept	0.0000 (0.9420)	6.85E-05 (0.7588)	-0.0002 (0.7474)
$R\_FTSE_{Large,\ t-1}$	-0.0426 (0.0016)	-	-0.0665 (0.0021)
$R\_FTSE_{Large,\ t-2}$	0.0592 (0.0000)	-	0.0941 (0.0000)
$R\_FTSE_{Large,\ t-4}$	0.0421 (0.0033)	-	-
$R\_FTSE_{Large,\ t-5}$	0.0427 (0.0036)	-	0.0803 (0.0042)
$R\_FTSE_{Large,\ t-6}$	-0.0874 (0.0000)	-	-0.1274 (0.0000)
$R\_FTSE_{Large,\ t-9}$	0.0581 (0.0000)	-	0.1115 (0.0000)
$R\_FTSE_{Large,\ t-10}$	-0.0517 (0.0003)	-	-0.1068 (0.0000)
$\Delta TVIX_{\ t}$	-0.0189***	-0.0061**	-0.0544***

Equations	**May 6, 2014 to December 27, 2023**	**May 6, 2014 to December 30, 2019**	**January 1, 2020 to December 27, 2023**
	(0.0000)	(0.0108)	(0.0000)
$\Delta TVIX_{t-1}$	-0.0060*** (0.0005)	-0.0011 (0.6688)	-0.0085*** (0.0053)
$\Delta TVIX_{t-2}$	-0.0018 (0.4018)	0.0015 (0.5540)	-0.005248 (0.1588)
$\Delta TVIX_{t-3}$	0.0025 (0.1547)	0.0019 (0.4318)	0.003499 (0.2758)
Adj. R^2	0.0462	0.0028	0.1483
Panel B: $R\_FTSE_{Mid,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Mid,\ t-lag}) + C_{tvix,0}(\Delta TVIX_{t}) + \sum^{N=3} C_{tvix,n}(\Delta TVIX_{t-n}) + e_t$			
Intercept	0.0000 (0.9425)	0.0001 (0.5953)	-0.0001 (0.7176)
$R\_FTSE_{Mid,\ t-1}$	-	0.0724 (0.0043)	-
$R\_FTSE_{Mid,\ t-2}$	0.0429 (0.0002)	-	-
$R\_FTSE_{Mid,\ t-5}$	0.0558 (0.0000)	-	0.0797 (0.0009)
$R\_FTSE_{Mid,\ t-6}$	-0.0707 (0.0000)	-	-0.0802 (0.0000)
$R\_FTSE_{Mid,\ t-9}$	-0.0390 (0.0042)	-	-
$R\_FTSE_{Mid,\ t-11}$	0.0870 (0.0000)	-	-
$\Delta TVIX_{t}$	-0.0236*** (0.0000)	-0.0085*** (0.0000)	-0.0696*** (0.0000)
$\Delta TVIX_{t-1}$	-0.0064*** (0.0006)	-0.0010 (0.6671)	-0.0049 (0.2554)
$\Delta TVIX_{t-2}$	-0.0028 (0.1912)	0.0024 (0.3058)	-0.0083*** (0.0064)
$\Delta TVIX_{t-3}$	-0.0003 (0.8645)	0.0020 (0.3430)	-0.0051* (0.0856)
Adj. R^2	0.0645	0.0149	0.1822
Panel C: $R\_FTSE_{Small,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Small,\ t-lag}) + C_{tvix,0}(\Delta TVIX_{t}) + \sum^{N=3} C_{tvix,n}(\Delta TVIX_{t-n}) + e_t$			
Intercept	0.0000 (0.9095)	-0.0001 (0.6440)	0.0003 (0.5203)
$R\_FTSE_{Small,\ t-1}$	0.0907 (0.0000)	0.1030 (0.0000_	0.1138 (0.0000)

Equations	**May 6, 2014 to December 27, 2023**	**May 6, 2014 to December 30, 2019**	**January 1, 2020 to December 27, 2023**
$R\_FTSE_{Small, t-2}$	0.0419 (0.0039)	-	-
$R\_FTSE_{Small, t-4}$	0.0371 (0.0083)	-	-
$R\_FTSE_{Small, t-5}$	0.0404 (0.0180)	-	-
$R\_FTSE_{Small, t-6}$	-0.0630 (0.0000)	-	-0.0852 (0.0000)
$\Delta TVIX_{t}$	-0.0297*** (0.0000)	-0.0127*** (0.0000)	-0.0792*** (0.0000)
$\Delta TVIX_{t-1}$	-0.0080*** (0.0001)	-0.0018 (0.4926)	-0.0091** (0.0292)
$\Delta TVIX_{t-2}$	-0.0037 (0.1346)	0.0018 (0.4590)	-0.0114*** (0.0086)
$\Delta TVIX_{t-3}$	0.0014 (0.4091)	0.0026 (0.2335)	-0.0042 (0.1933)
Adj. R^2	0.0775	0.0304	0.1983

Note: The reported statistics are the daily TVIX and returns based on FTSE SET Index. In the table, asterisks (*) are used to indicate statistical significance; ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are p-values.

The regression analysis using a multiple regression model as shown in Table 5 explores the impact of various factors on stock returns across market capitalizations (large, mid, and small cap) for the full sample period (May 2014 - Dec 2023), pre-COVID-19 and post-COVID-19 eras. Confirming the prior findings, changes in TVIX have a negative and statistically significant (1% level) impact on returns for all market capitalizations in the full sample. Additionally, the return on oil prices also has a negative and significant (1% level for large-cap, 10% level for mid-cap, and 5% level for small-cap) influence across the full sample. Interestingly, the effects of other included variables like Geopolitical Risk (GPR) and returns on gold prices were not statistically significant for most cases in the full sample analysis.

Further analysis reveals a difference in the influence of these factors between pre- and post-COVID-19 periods. While TVIX remains a significant negative factor for returns in both periods (mostly at the 5% level), the impact of other variables exhibited variations. Pre-COVID-19, the return on oil prices held the strongest negative influence (1% level) for large-cap stocks, followed by Geopolitical Risk (5% level) and gold prices (10% level). For mid and small-cap stocks in the pre-COVID era, GPR becomes significant at 1% level, at the same time, TVIX and oil prices showed statistically significant negative relationships with returns (at 5% and 10% level respectively).

The post-COVID-19 period presents a distinct picture. The influence of oil prices becomes insignificant for large-cap stocks, while the change in TVIX and return on gold prices emerges as a significant negative factor (1% level). Geopolitical Risk also becomes a positive and significant factor (10% level) for large-cap returns in the post-COVID era. Interestingly, for mid and small-cap stocks in the post-COVID period, only TVIX maintains a statistically significant negative relationship with returns (1% level).

Table 5: The effects of TVIX and exogenous variables on Returns of FTSE SET Index series

Equations	**May 2014 to December 2023**	**May 2014 to December 2019**	**January 2020 to December 2023**
Panel A: $R\_FTSE_{Large,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Large,\ t\text{-}lag}) + C_{tvix}(\Delta TVIX_t) + C_{gpr}(\Delta GPR_t) + C_{gold}(GOLD_t) + C_{oil}(OIL_t) + C_{covid}(COVID19_t) + e_t$			
Intercept	-0.0022 (0.4037)	0.0014 (0.7241)	0.0031 (0.2764)
$R\_FTSE_{Large,\ t-1}$	-	0.2295 (0.0793)	-
$R\_FTSE_{Large,\ t-3}$	-	-	-0.6884 (0.0002)
$R\_FTSE_{Large,\ t-6}$	-	-	-0.6597 (0.0001)
$R\_FTSE_{Large,\ t-7}$	0.2555 (0.0070)	-	-
$R\_FTSE_{Large,\ t-8}$	-0.4158 (0.0000)	-	-
$\Delta TVIX_t$	-0.0614*** (0.0000)	-0.0438** (0.0210)	-0.1093*** (0.0010)
ΔGPR_t	0.0407 (0.5459)	-0.2552** (0.0270)	0.2384* (0.0937)
$GOLD_t$	-0.0533 (0.6161)	0.2331* (0.0789)	-0.7118 *** (0.0002)
OIL_t	0.0787*** (0.0012)	0.1290*** (0.0003)	0.0619 (0.1470)
$COVID19_t$	-	-	-0.0052 (0.2419)
Adj. R^2	0.4404	0.3312	0.4876
Panel B: $R\_FTSE_{Mid,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Mid,\ t\text{-}lag}) + C_{tvix}(\Delta TVIX_t) + C_{gpr}(\Delta GPR_t) + C_{gold}(GOLD_t) + C_{oil}(OIL_t) + C_{covid}(COVID19_t) + e_t$			
Intercept	-0.0024 (0.2580)	0.0022 (0.3887)	0.0268 (0.7276)
$R\_FTSE_{Mid,\ t-4}$	0.1962 (0.0447)	-	-
$R\_FTSE_{Mid,\ t-6}$	-0.2662 (0.0066)	-0.3027 (0.0213)	-

Equations	May 2014 to December 2023	May 2014 to December 2019	January 2020 to December 2023
$R\_FTSE_{Mid, t-8}$	-0.3928 (0.0001)	-	-
$\Delta TVIX_t$	-0.0807*** (0.0000)	-0.0432** (0.0300)	-0.1136*** (0.0004)
ΔGPR_t	0.0462 (0.4976)	-0.0057 (0.1168)	0.1387 (0.3634)
$GOLD_t$	0.0217 (0.8374)	0.1787 (0.1981)	-0.2371 (0.2932)
OIL_t	0.0595** (0.0117)	0.0691* (0.0501)	0.0611 (0.1601)
$COVID19_t$	-	-	0.0031 (0.6001)
Adj. R^2	0.4313	0.2105	0.4448
Panel C: $R\_FTSE_{Small,t} = C_0 + \sum^{N=n} C_n(R\_FTSE_{Small, t-lag}) + C_{tvix}(\Delta TVIX_t) + C_{gpr}(\Delta GPR_t) + C_{gold}(GOLD_t) + C_{oil}(OIL_t) + C_{covid}(COVID19_t) + e_t$			
Intercept	-0.0025 (0.5389)	-0.0017 (0.8558)	0.0058 (0.4211)
$R\_FTSE_{Small, t-1}$	-	0.2967 (0.0180)	-
$R\_FTSE_{Small, t-9}$	-	0.3081 (0.0268)	-
$\Delta TVIX_t$	-0.1057*** (0.0000)	-0.0426* (0.0882)	-0.1618*** (0.0000)
ΔGPR_t	-0.0964 (0.3209)	-0.4692 *** (0.0019)	0.0690 (0.7041)
$GOLD_t$	0.1929 (0.2244)	0.2637 (0.1851)	-0.0773 (0.7730)
OIL_t	0.0784** (0.0278)	0.0794* (0.0816)	0.0515 (0.3197)
$COVID19_t$	-	-	0.0031 (0.6656)
Adj. R^2	0.3344	0.2287	0.4878

Note: The reported statistics have a monthly frequency. In the table, asterisks (*) are used to indicate statistical significance; ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are p-values.

It's important to note that these findings highlight the most statistically significant factors based on the chosen significance levels (1%, 5%, and 10%). Further investigation might explore the potential influence of other variables not included in this model.

5. Conclusion

This study confirms a significant negative impact of changes in the Thailand Volatility Index (TVIX) on returns across all FTSE SET Index series (large, mid, and small cap). This effect is particularly pronounced for smaller companies and strengthens in the post-pandemic era. Furthermore, the increasing importance of past volatility (lagged TVIX terms) in explaining returns, especially for smaller stocks post-pandemic, underscores their heightened sensitivity to volatility fluctuations. While TVIX remains a key factor, the pre-pandemic analysis of large-cap stocks highlights the potential influence of other variables like Geopolitical Risk (GPR) and gold prices. Interestingly, the inclusion of COVID-19 case numbers in the post-pandemic model did not significantly influence returns. This suggests that the direct impact of COVID-19 cases on returns within the FTSE SET Index might be less prominent than other factors.

These findings offer valuable insights for investors and portfolio managers navigating the Thai stock market. Understanding the dynamic relationship between volatility, market capitalization, and other relevant factors can inform investment decisions, particularly in the post-pandemic environment with its heightened volatility. For investors, these results underscore the need for heightened caution when investing in small-cap stocks during periods of elevated market volatility, as they are more susceptible to adverse market conditions. Investors should also consider diversifying their portfolios to include assets that are less volatile or negatively correlated with market risk, such as gold, which may offer a hedge against rising volatility in smaller market segments. Moreover, investors might benefit from monitoring geopolitical risks and oil price fluctuations, which could provide early indicators of shifts in stock returns. Utilizing tools such as volatility indices (e.g., TVIX) and sentiment analysis of news related to geopolitical risks could help investors better manage risk exposure and make more informed decisions in uncertain market conditions. Also, portfolio managers should remain adaptive to the post-pandemic dynamics and prepare for future volatility spikes by employing advanced models like GARCH or VAR to account for volatility clustering. This will enable a more dynamic approach to risk management, ensuring portfolios remain resilient against sudden market shocks

Somehow, the model used in this study seems not fully capture all explanatory factors such as COVID-19 case number in Thailand or the change of TVIX in the past. To further explore potential influences, as a recommendation, future research could utilize Natural Language Processing (NLP) to analyze sentiment in financial news and identify broader market sentiment or company-specific events that might correlate with returns. Additionally, employing alternative regression models like GARCH or VAR could provide more comprehensive insights into volatility clustering and dynamic relationships between TVIX and other potential explanatory variables. Expanding the analysis to include other markets, incorporating social media data and economic indicators, and investigating potential non-linear relationships between TVIX and returns are also promising avenues for future research. By addressing these limitations and exploring these avenues, it can provide more comprehensive understanding of the factors influencing stock returns and the role of TVIX in these relationships, ultimately providing valuable insights for investors and market participants.

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Enhancing Stock Return Predictions in Asset Allocation: Integrating Black-Litterman Model with Deep Learning Techniques

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Abstract

Advances in technology, particularly artificial intelligence (AI), have permeated various fields including finance, and become a crucial component of financial technology. This paper explores using Long Short-Term Memory (LSTM) deep learning with the Black-Litterman model for asset allocation, leveraging LSTM's ability to analyze historical price data and generate unbiased investor views. Focusing on the mai and SET50 markets within The Stock Exchange of Thailand (SET), the study rebalances portfolios every six months and evaluates performance through backtesting over three years (2021-2023). The Black-Litterman portfolios are compared to equal weight and mean variance strategies. Results indicate that forecasts generated from LSTM were more accurate for the mai market than the SET50 market, although overall accuracy for both markets was lower than expected, suggesting historical price data alone may be insufficient for six-month predictions. The BL-mai portfolio's performance, measured by Sharpe Ratio, matched that of the mean variance portfolio but was lower than the equal weight portfolio. Additionally, the BL-SET50 portfolio did not show significant advantage over two benchmarks. Further improvements are needed for better predictive accuracy and performance.

Keywords: Asset Allocation, Black-Litterman Model, Long short-term memory, LSTM, Machine Learning, Stock Price Prediction

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การประยุกต์ใช้ LSTM ร่วมกับ Black-Litterman Model

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บทคัดย่อ

ในปัจจุบันพัฒนาการของเทคโนโลยี โดยเฉพาะปัญญาประดิษฐ์ (AI) ได้เข้าไปมีบทบาทสำคัญในหลากหลายสาขา รวมถึงสาขาทางด้านการเงิน จนกลายเป็นส่วนสำคัญของการพัฒนาเทคโนโลยีทางการเงิน (FinTech) ส่งผลให้ให้งานวิจัยนี้ มีความต้องการที่จะศึกษาการใช้ประโยชน์จาก Long Short-Term Memory (LSTM) ซึ่งเป็นเทคนิค Deep Learning มาประยุกต์ใช้ร่วมกับ Black-Litterman model เพื่อทำการจัดสรรสินทรัพย์ในการลงทุนในพอร์ตโฟลิโอ โดยอาศัย ความสามารถของ LSTM ในการวิเคราะห์ข้อมูลราคาหุ้นย้อนหลัง เพื่อสร้าง investor’s view ที่เป็นกลาง เพื่อที่จะในไปใช้ใน Black-Litterman model งานวิจัยนี้เน้นการศึกษาในตลาด mai และ SET50 ของตลาดหลักทรัพย์แห่งประเทศไทย (SET) โดยมีพอร์ตโฟลิโอจะมีการปรับสมดุลตาม Black-Litterman model ทุกๆ 6 เดือน และประเมินผลการดำเนินงานด้วยการทำ Backtesting ในช่วงเวลา 3 ปี (2021-2023) ผลของการจัดสรรสินทรัพย์ตาม Black-Litterman model จะถูกนำไปเปรียบเทียบกับ การจัดสรรสินทรัพย์แบบ equal weighted และ mean variance โดยจากผลการค้นคว้าพบว่า การพยากรณ์ราคาหุ้นโดย LSTM แม่นยำกว่าในตลาด mai เมื่อเทียบกับตลาด SET50 แม้ว่าโดยรวมแล้วความแม่นยำในการพยากรณ์ทั้งสองตลาดจะต่ำกว่าที่คาดการณ์ไว้ ซึ่งบ่งชี้ว่าข้อมูลราคาหุ้นย้อนหลัง เพียงอย่างเดียว อาจไม่เพียงพอสำหรับการคาดการณ์ราคาหุ้นในอีก 6 เดือนข้างหน้า และ พอร์ตโฟลิโอ BL-mai ซึ่งวัดประสิทธิภาพโดย Sharpe Ratio มีค่าใกล้เคียงกับพอร์ตโฟลิโอแบบ mean variance แต่ต่ำกว่าพอร์ตโฟลิโอแบบ equal weighted

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ผลการศึกษาเพิ่มเติมพบว่า พอร์ตโฟลิโอ BL-SET50 ไม่มีข้อได้เปรียบที่เหนือกว่าเมื่อเทียบกับ เกณฑ์การเปรียบเทียบทั้งสองแบบ ซึ่งชี้ให้เห็นว่าจำเป็นต้องมีการพัฒนาโมเดลเพิ่มเติมเพื่อให้มีความแม่นยำในการพยากรณ์ และประสิทธิภาพการลงทุนที่ดีขึ้น

คำสำคัญ: การจัดสรรสินทรัพย์, การพยากรณ์ราคาหุ้น, การเรียนรู้ของเครื่อง, แบบจำลอง Black-Litterman, แบบจำลอง Long Short-Term Memory

1. Introduction

The advances in technology, especially artificial intelligence (AI), have been spread in many fields including the financial field. A branch of computer science called artificial intelligence, or AI, focuses on building intelligent machines that behave, think, and perform similarly to humans. Machines are able to train themselves, organize and understand data, and create predictions based on the data, the process known as machine learning. Thus, it has become a crucial component in financial technology. RoboAdvisor, Open Banking, Chatbots, and financial technology (Fintech) companies are popular trends and research topics recently. This research focuses on adoption of machine learning with asset allocation models. Asset allocation is a strategic approach in which investors distribute their portfolios across various assets. This process aims to find a balance between risks and rewards, by considering various factors such as financial goals, risk tolerance, and the investment horizon of investors. Asset allocation becomes particularly significant for investors aiming to optimize portfolios, ensuring that the asset mix chosen is adequate for their personal condition and goals. Effective asset allocation is critical for investors trying to attain the desired risk-return of their portfolio.

The Modern Portfolio Theory (MPT) developed by Markowitz is the most straightforward and widely used asset allocation approach. Modern portfolio theory proposes a diversification concept that attempts to maximize the expected return of a portfolio for a given level of risk or, alternatively, minimize the risk for a given level of expected return. Based on Markowitz's concept, economists Fischer Black and Robert Litterman developed the Black-Litterman model. The Black-Litterman model extended the modern portfolio theory by incorporating the investor's views of future expected returns in optimizing the portfolio.

This study aims to integrate the Black-Litterman model with the Long-Short-Term Memory (LSTM) deep learning approach. The integration of these approaches intends to take advantage of the computer power in generating unbiased opinions of future stock performance, which will be used as an investor view in Black-Litterman model, rather than acquiring it from investment experts. The strengths of LSTM in capturing complex correlations across historical stock prices over the time period will be utilized in predicting stock prices in the future period. By integrating the LSTM model predictions into the Black-Litterman model, the research intends to provide investors with more trustworthy and less biased viewpoints in optimizing asset allocation. This study focuses specifically on The Stock Exchange of Thailand (SET). The LSTM model is trained using two datasets of historical prices of selected stocks, the first dataset comprises the selected stocks from mai market, while the second consists of the selected stock from SET50 market. The main objective is to develop a comprehensive model in Python that not only predicts stock prices but also seamlessly incorporates the prediction into the Black-Litterman model for enhanced asset allocation. The result performance of the portfolio will be compared with equally weighted and mean-variance allocation which evaluates using annual return and Sharpe ratio.

1.1 Objective

This paper has three objectives: first, to develop the most accurate and efficient machine learning model for stock price prediction using historical price data; second, to demonstrate the effectiveness of a Black-Litterman model incorporating machine learning over a simple asset allocation approach; third, to evaluate the performance of applying machine learning to the Black-Litterman model in the MAI market compared to the SET50 market.

1.2 Significant of Research

In mai market, there is a lack of stock analysis reports from the analyst. According to research of TDRI (2024), the number of stock analysis reports published on the Settrade website, out of approximately 840 listed stocks, less than 1 in 4 have stock analysis reports. From these portions, only three to five are stock analysis reports on MAI stocks. This is because the analysis of small-cap stocks is often considered not worth the cost and time required to gather data, which typically involves interviews and requests for information from companies. This is due to several factors based on the size of the firm. Many small-cap companies do not have well-developed websites or investor relations departments, making it difficult to obtain information about their businesses. Additionally, small-cap stocks typically have lower liquidity than large-cap stocks, complicating the process of buying and selling these stocks. Furthermore, small-cap companies often present poor fundamentals and higher financial risk relative to their large-cap counterparts, making them less attractive to many investors. Despite these challenges, a stock performance report prepared by SET found a substantial growth potential within the MAI market. Over the past ten years, more than half of the IPO stocks of 21 listed companies on the MAI market had grown enough to move to the SET within only about 3 years. This finding highlights the potential of small-cap stocks on the MAI market, suggesting that, despite the inherent difficulties, they can offer considerable growth opportunities for investors. In larger markets, such as the Stock Exchange of Thailand (SET), numerous stock analysis reports are available due to the substantial market capitalization and trading volume. Despite the abundance of these reports, their recommendations often do not respond rapidly enough to capture market changes. Consequently, relying on these reports for rebalancing and adjusting portfolio according Black-Litterman may not be the most effective approach.

In Black-Litterman model, the investor’s views are normally obtained from the stock analysis report from the analyst. But due to the lack of this report in mai market, this study fills this gap by integrating a deep learning approach, specifically an LSTM model, to generate investor views based on historical price data. This approach offers an alternative to traditional methods and potentially provides valuable insights for asset allocation decisions. By demonstrating the feasibility of generating investor views through machine learning, this study aims to contribute to a more vibrant research landscape for the mai market. The availability of such information could encourage further analysis and potentially attract more investor attention to the market's potential.

2. Literature review

The related literature and theories in incorporation of Black-Litterman and machine learning model will be discussed in this section. The related theory will be presented in five parts. The first part investigates the Black-Litterman model. The second part discusses the deep learning model for predicting stock prices. The third part defines benchmark portfolios. The fourth part presents the evaluation metrics of the portfolio performance. Lastly, the fifth part discusses related literature.

2.1 Black-Litterman Model

The Black-Litterman model has been introduced since 1990, by Goldman Sachs economists Fischer Black and Robert Litterman. The model is an asset allocation model that overcomes the problem of unintuitive, highly concentrated portfolios, input-sensitivity, and estimation error maximization. These three problems occur with the mean-variance optimization in modern portfolio theory of Markowitz where return is maximized for a given level of risk. The Modern Portfolio Theory has limitations because it relies only on historical market data and assumes that these past returns will persist into the future. In contrast, the Black-Litterman model provides a more dynamic framework, allowing investors to incorporate their own views into the analysis. This enables the optimization of asset allocation based on the investor's unique perspectives, offering a more flexible and personalized approach. The Black-Litterman model is developed from modern portfolio theory, the traditional Mean-Variance Optimization model. This model uses Bayesian theory to incorporate the views on future outlook of an investor in the portfolio optimization process. The optimal portfolio weight is determined based on the expected excess return calculated from the model. The procedure of Black-Litterman model is shown in figure 1.

The first step in Black-Litterman model is to calculate the risk aversion coefficient, which is the rate at which an investor will forego expected return for less variance, and it can be calculated by the following formula.

$$\lambda = \frac{E(r_m)-r_f}{\sigma_m^2}$$

$E(r_m)$: Expected market returns

r_f : Risk-free rate

${\sigma^2}_m$: Variance of market

Then calculate the Implied Equilibrium Excess Return, also referred to as the prior expected return, which the formula is given below.

$$\Pi = \lambda \Sigma w_{mkt}$$

Π : The Implied Excess Equilibrium Return

λ : The risk aversion coefficient

Σ : The covariance matrix of excess returns

w_{mkt} : The market capitalization weight of the assets

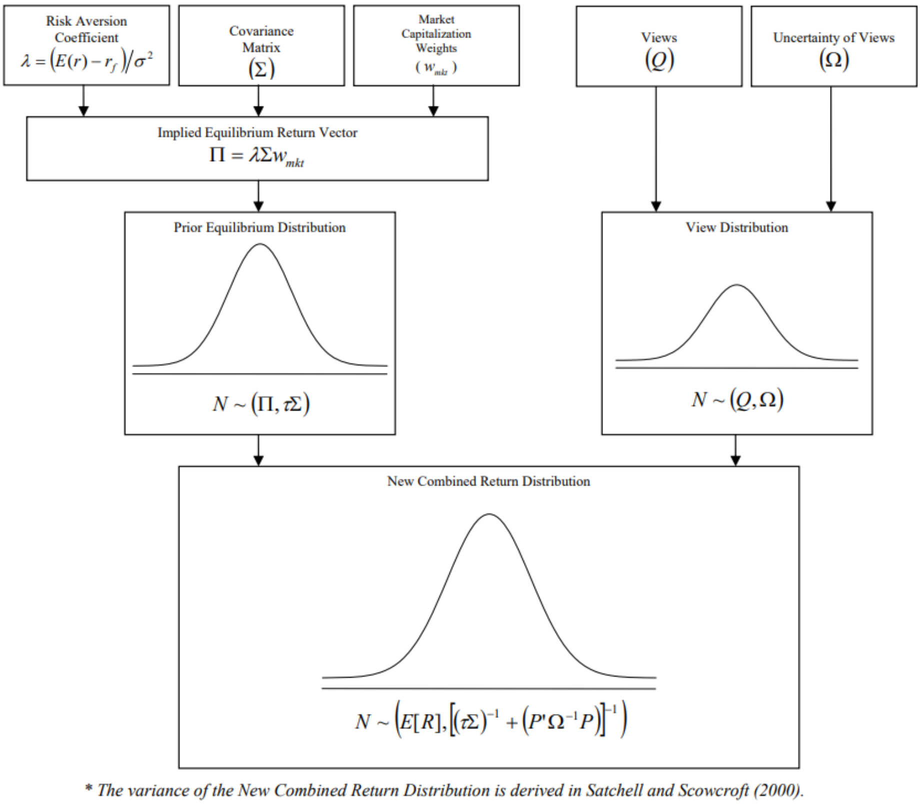

Figure 1: The procedure of Black-Litterman model. Retrieved from A Step-by-Step Guide to the Black-Litterman Model (Thomas M. Idzorek, 2005)

Next step, generating the view matrix and the link matrix which will map the view into each stock as a matrix. The uncertainty of the view, represented by the variance, Ω, can be established through expert opinion or calculated using the following formula.

$$\Omega = diag(P(\tau\Sigma)P^T$$

Ω : The uncertainty of views

P : The Link matrix

τ : A scalar

Σ : The covariance matrix of excess returns

After that, The new expected excess return, also referred to as the posterior expected return, from Black-Litterman can be calculate by following formula;

$$E[R] = [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P^T\Omega^{-1}Q]$$

E[R] : The new Expected Excess Return

τ : A scalar

Σ : The covariance matrix of excess returns

P : The link matrix

Ω : The uncertainty of views

Π : The Implied Excess Equilibrium Return

Q : The View Vector

2.2 Long Short-Term Memory Model

Long Short-Term Memory, or LSTM, is a more advanced version of recurrent neural networks (RNN) that can handle the vanishing gradient problem that is faced in RNN. Hochreiter and Schmidhuber created LSTM in 1997 to address an issue caused by standard RNNs and machine learning methods. RNNs remember the previous information and utilize it when assessing current input, but because of vanishing gradient problems, RNN cannot remember long-term dependencies. By introducing feedback connections, LSTM has the capability to handle entire sequences of data rather than simply individual data points, allowing it to capture long-term dependencies. Because of its capacity to extract valuable insights from sequential data, LSTM is particularly effective in analyzing and forecasting patterns in sequential data such as time series. LSTM operates similarly to an RNN cell. It manages information and determines which information to forget and which to remember in order to identify long-term dependencies or trends using several layers and gates. The LSTM network consists of three gates that control the flow of data in and out of the memory cell. The first gate is known as the Forget gate, the second as the Input gate, and the final as the Output gate.

2.2.1 Forget Gate

This cell determines whether the information from the previous timestamp should be remembered or is irrelevant and can be ignored. The values are passed into a sigmoid function, which will generate only numbers 0 and 1. The number 0 indicates that past knowledge can be forgotten since newer information is more important information. The first number suggests that the prior knowledge should be preserved as it is still beneficial.

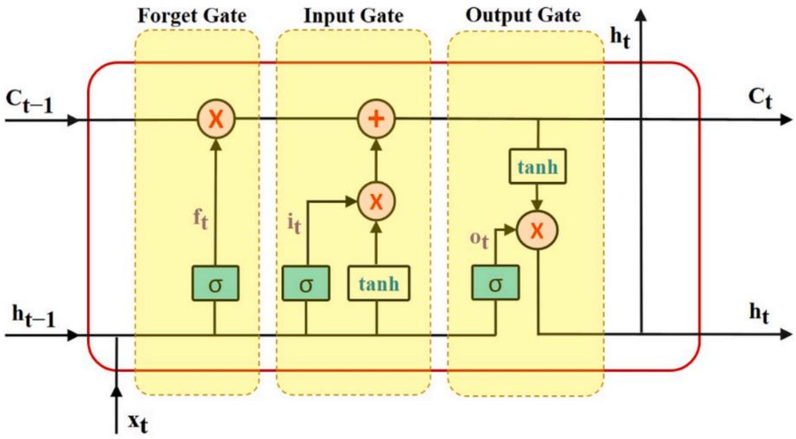

Figure 2: Long Short-Term Memory Model Architecture. Retrieved from Intelligent Asset Allocation using Predictions of Deep Frequency Decomposition (Rezaei et al., 2021)

2.2.2 Input Gate

The cell learns new information from the input and determines what information will be added to the long-term memory of the model by determining how valuable the current input is to solving the assigned task. The current input is multiplied by the hidden state and latest weight matrix. All important information from the Input Gate is subsequently added to the cell state, resulting in the new cell state C(t). This new cell state is now the long-term memory's current state and will be used in future iterations.

2.2.3 Output Gate

The output of the LSTM model is then computed in the Hidden State. The sigmoid function determines what information can pass through the output gate, and the cell state is multiplied once the tanh function activates. The cell passes the latest information from the current timestamp to the next timestamp.

2.3 Benchmark Portfolio

2.3.1 Mean-Variance Portfolio

Mean-Variance analysis is a fundamental of Modern Portfolio Theory (MPT) developed by Markowitz. This framework seeks to optimize the balance between the expected return, or mean, and the risk, or variance, of the investment portfolio. This enables investors to customize an investment strategy according to the amount of risk they are willing to take in exchange for different levels of return. There are two main components of mean-variance analysis: variance and expected return. Variance measures the degree to which actual returns may differ from the expected return. Expected return refers to the average return investors anticipate from the entire portfolio over a specific timeframe, which represents the overall profitability investors expect to achieve from the investments.

2.3.2 Equal Weighted Portfolio

An equal-weighted portfolio is an investment strategy where all assets in the portfolio are allocated the same proportion of the total investment. This method ensures that each asset has an equal impact on the portfolio's overall performance, regardless of market capitalization or other factors.

2.4 Portfolio Evaluation Metrics

2.4.1 Annual Return

An investment portfolio's annual return is a representation of its total return or loss over a one-year timeframe, presented as a percentage of the initial investment.

2.4.2 Variance

Variance captures the volatility or spread of possible returns around the expected return which is also known as risk. It essentially measures how much actual returns might deviate from the expected return.

2.4.3 Sharpe Ratio

The Sharpe ratio calculates a portfolio's excess return per unit of risk. A greater Sharpe ratio suggests better risk-adjusted performance since it shows that the portfolio earns higher returns for each unit of risk taken.

$$Sharpe\ Ratio = \frac{Portfolio\ Return - Risk\ free\ rate}{Portfolio\ Standard\ Deviation}$$

2.5 Related Literature

Rezaei et al. (2021) introduced a novel hybrid deep learning model for stock prediction and incorporated these predictions as investors' views in Black-Litterman asset allocation model. The hybrid model comprises Complete Ensemble Empirical Mode Decomposition (CEEMD), convolutional neural network (CNN) and Long Short-term Memory (LSTM) models. The portfolio in this research consists of the top 10 highest return stocks from top 20 highest trading volume stocks of the Dow Jones index. This research found that the Black-Litterman portfolio based on the predictions of the hybrid CEEMD-CNN-LSTM model constructed portfolios with high return, low extreme allocation, low risk, and also outperformed the mean-variance portfolio, equal-weighted portfolio. Li and Chen (2019) proposes a programmatic ETF portfolio configuration that combines Support Vector Regression (SVR) and Black-Litterman models, based on ETF funds issued in Taiwan. The results of the study showed that under the same risk value, the SVR with Black-Litterman two stage model proposed by this study has a higher return rate than historical return and implied return. Li et al. (2022) developed a random forest based Black-Litterman model, in which the view vector is derived from the predicted asset returns generated by Random Forests (RF). The study discovered that a random forest with the Black-Litterman model achieved superior portfolio performance in the Chinese stock market. This is evidenced by higher cumulative returns and improved Sharpe ratios compared to the classic mean-variance model. Punyaleadtip (2022) examined the performance of the Black-Litterman model integrating investor's view derived from a combination of two deep learning approaches: Long Short-Term Memory (LSTM) and Support Vector Regression (SVR). The study investigated these models in two different markets: the Dow Jones Index (DJI) in the USA and the SET100 index in Thailand. The LSTM model is used to forecast the technical indicators, then use the forecasted technical indicator to calculate the future price. The technical indicators used in this paper group into four types: cycle (e.g., Hilbert Transform - Dominant Cycle Period), momentum (e.g., Relative Strength Index), trend (e.g., Exponential Moving Average), and volatility (e.g., Average True Range). This research found that Black-Litterman portfolios that integrate LSTM and SVR models for calculating investor's view yielded higher returns than both the DJI and SET100 indices, but experienced greater negative maximum drawdown.

Nikou et al. (2019) evaluate the prediction power of machine learning models, i.e. Artificial neural network (ANN), SVR, RF, and Long Short Term Memory (LSTM), in a stock market based on iShares MSCI United Kingdom exchange traded fund. The results of the study show that the LSTM is better in prediction of the close price of iShares MSCI United Kingdom than the other methods. Hiransha et al. (2018) investigate the performance of deep learning algorithms, i.e. Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), LSTM, and CNN for predicting stock price of National Stock Exchange of India (NSE) and the New York Stock Exchange (NYSE). The results show that all deep learning models are better than ARIMA and CNN has performed better than other deep learning models. Demirel et al. (2021) compare the result of forecasted stock prices in Istanbul Stock Exchange National 100 Index by using machine learning methods, MLP and Support Vector Machines (SVM) models and deep learning algorithm, Long Short Term Memory (LSTM). The results of this study show that MLP and LSTM models become advantageous in estimating the stock prices compared to SVM models.

3. Methodology

Punyaleadtip (2022) examined the performance of applying the Black-Litterman model in Thailand, focusing on market indicators and global stocks. However, this research shifts the focus to individual stocks in Thailand's medium-small stock market to address the lack of timely analysis reports for smaller stocks, which obstruct the updating of investors' views. For larger stocks, although numerous analysis reports are available, the recommendations and target prices may not be updated quickly enough to effectively adjust the portfolio according to the Black-Litterman model.

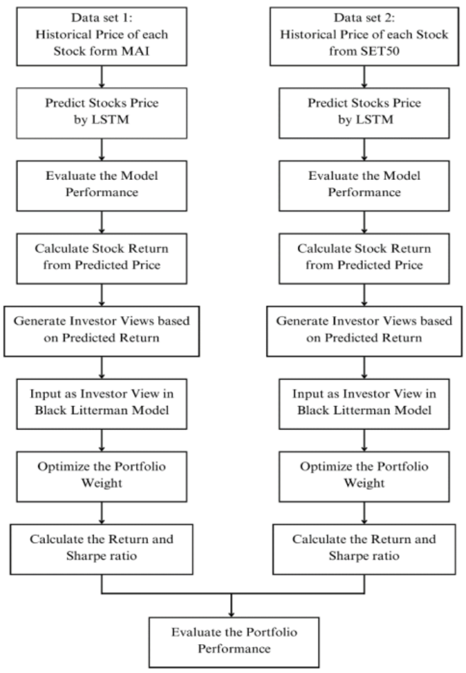

Figure 3: Research Procedure

This research proposes a development of a Long Short-Term Memory (LSTM) based Black-Litterman model, in which the view vector is generated based on the predicted asset returns obtained by the Long Short Term Memory model. Then construct the portfolio which obtains the optimal weight from the LSTM-Black-Litterman model. The research procedure is visualized in figure 3 which can be separated into two main parts. The first part is to develop the LSTM model to predict the stock price based on two different markets: mai and SET50. The LSTM model will be evaluated based on the Root Mean Squared Error (RMSE). The second part, utilizing the predicted price from the first part in Black-Litterman model. Before passing to the Black-Litterman, have to transform it to the form of investor views by converting the predicted price to return and construct the investor views based on that return. Then input the views into the Black-Litterman model and get the optimal portfolio weight as an output. Last step is to evaluate the portfolio performance by comparing with the equal weighted portfolio and mean variance portfolio by using Annual return and Sharpe ratio as evaluation metrics.

3.1 Portfolio Construction

This study adopted a portfolio construction strategy that focused on selecting three stocks from the ten largest companies by market capitalization within each market. The selection criteria prioritize stocks with comparable market capitalizations, which promotes balanced portfolio weighting and mitigates the risk associated with overconcentration in any single large-cap company. Additionally, the analysis focuses on companies with at least five years of historical stock price data to facilitate robust performance of the model.

3.1.1 MAI market

The Market for Alternative Investment, or mai, is a stock exchange in Thailand, which was established by the Stock Exchange of Thailand (SET) in 1998. This market serves as an alternative platform for smaller and medium-sized enterprises (SMEs) to raise capital. Three stocks that were selected are listed in table 1.

Table 1: List of Stocks in mai Portfolio

Stock Name	Market Capitalization as of December 2020	First Trading Day
AU	9,461.23 M. Baht	December 23, 2016
SPA	7,353 M. Baht	October 31, 2014
XO	5,436.98 M. Baht	August 25, 2014

3.1.2 SET50 Index

SET50 or Stock Exchange of Thailand 50 Index, is an index that tracks the performance of the 50 largest and most liquid companies listed on the Stock Exchange of Thailand (SET). Three stocks that were selected are listed in table 2.

Table 2: List of Stocks in SET50 Portfolio

Stock Name	**Market Capitalization** as of December 2020	**First Trading Day**
ADVANC	515,911.67 M. Baht	November 5, 1991
CPALL	622,079.77 M. Baht	October 14, 2003
PTTEP	452,578.34 M. Baht	June 10, 1993

3.2 Investment Strategy

To ensure a fair comparison of performance between the two portfolios employed in this research, both portfolios will adhere to an identical investment strategy. Each portfolio will consist of three stocks from each market. In order to maintain portfolio equilibrium and capture market movements, portfolio rebalancing will occur on a semi-annual basis, specifically on January 1st and July 1st of each year. During rebalancing, the entire value of the portfolio will be reinvested for the next period. This ensures that all capital gains or losses accumulated during the previous period are fully captured and incorporated into the subsequent period's performance.

3.3 LSTM model

Long Short-Term Memory (LSTM) was employed in this research to forecast stock prices for a six-month horizon in each period. The models leverage all available historical data for each stock, starting from the initial trading day to the current date, and will be trained separately in each period. The LSTM architecture consisted of four LSTM layers, each incorporating a 20% dropout rate. The root mean square error (RMSE) was utilized to monitor the training process. The total number of trainable parameters within the model is 71,357 parameters. A dropout rate of 20% was implemented within each LSTM layer, to mitigate overfitting problems. This technique randomly drops a portion of the neurons during training, effectively reducing model complexity and preventing it from memorizing the training data too precisely. An early stopping mechanism was also incorporated into the model. During training, this method keeps track of the model's performance on a validation set. If the validation performance fails to improve for a predefined number of iterations, which in this research set as three, the training process is automatically terminated. This helps to prevent overtraining and ensures the model generalizes well to unseen data.

3.4 Black-Litterman

After forecasting the stock price, the investor’s view will be determined by calculating the percentage change between the predicted price and the purchase price. This metric reflects the potential profitability or loss of the investment over the next period based on the forecasted price. The investor’s views are calculated as the following formula.

$$Investor's\ View = \frac{Last\ Predicted\ Price - Purchase\ Price}{Purchase\ Price}$$

The confidence of 70% was assigned to each investor view. This confidence level serves as a weighting factor in the process of combining the prior expected returns with the investor views to generate posterior expected returns.

The final weight of each stock in a portfolio will be optimized by maximizing Sharpe ratio with the maximum weight constraints of 70%. A maximum weight constraint mitigates the risk of overconcentration by ensuring that no single stock constitutes a significant portion of the overall portfolio value. This approach helps maintain portfolio diversification, which protects the portfolio from significant losses, and ensures that the portfolio's performance is not overly reliant on a single stock.

3.5 Performance Evaluation

The performance of the investment strategy will be evaluated through a backtesting approach spanning a three-year period from January 1, 2021, to December 31, 2023. This timeframe will be segmented into six distinct investment periods, as illustrated in Figure 4. The portfolio will be rebalanced at the end of each period. The performance of the Black-Litterman portfolios will be evaluated and compared to two benchmark allocation strategies which are equal weighted portfolio and mean variance portfolio. This evaluation will use key metrics as annual return and Sharpe ratio.

Investment Period 1	Investment Period 2	Investment Period 3	Investment Period 4	Investment Period 5	Investment Period 6
January 4, 2021 - July 1, 2021	July 1, 2021 - January 4, 2022	January 4, 2022 - July 1, 2022	July 1, 2022 - January 3, 2023	January 3, 2023 - July 3, 2023	July 3, 2023 - January 3, 2024

Figure 4: Investment Period

3.6 Data Collection

This research utilizes historical monthly closing price data for the selected stocks. The data was obtained from Yahoo Finance library in python and included the period from the initial trading date of each stock to the end of 2023. Additionally, historical market capitalization data for each stock was retrieved from SETSMART, covering the period from the last quarter of 2020 to the third quarter of 2023. Lastly, the daily index data for the mai and SET50 from 2011 to 2023 was downloaded from investing.com.

4. Results

The result of this research will be presented in two sections. The first section will focus on the performance of the LSTM model in forecasting stock prices. The second section will examine the optimal portfolio weights derived from the Black-Litterman model, which incorporates the investor views, generated by the LSTM model's predictions.

4.1 LSTM model

This section examines the effectiveness of the LSTM model in predicting future stock prices through the value of Root Mean Square Error (RMSE). RMSE is a statistical metric that quantifies the average magnitude of the difference between predicted and actual values, considering both the direction and size of the errors. Lower RMSE indicates a model that makes predictions closer to the actual values, signifying better overall performance. Table 3 presents the average RMSE for stock predictions in both the mai and SET50 markets.

Table 3: Average RMSE of Test Set for Stocks

	Stocks from mai			Stocks from SET50		
Stock Name	**AU**	**SPA**	**XO**	**ADVANC**	**CPALL**	**PTTEP**
Average RMSE	1.1330	1.4140	7.5349	45.0004	13.1404	33.0770

As presented in Table 3, the average RMSE for stocks within the mai market is noticeably lower compared to that observed for stocks in the SET50 market. This information implies a greater degree of accuracy for the model when predicting price movements within the mai market.

4.2 Black-Litterman Portfolio

4.2.1 Portfolio Allocation

Figures 5 and 6 illustrate the allocation weights for the two Black-Litterman portfolios under the study. Figure 5 details the weightings assigned to individual stocks within the Black-Litterman mai portfolio, while Figure 6 details the weightings for the Black-Litterman SET50 portfolio. Each figure presents the investment weight of each stock as a proportion of the total portfolio value for each investment period.

Figure 5 reveals that the BL-mai portfolio did not invest in any stocks during investment period 2. This decision came from predictions made by the LSTM model, which indicated potential price declines for all three stocks under consideration, AU, SPA, and XO. The Black-Litterman model incorporates this prediction by calculating negative posterior expected returns for all three stocks: -3.14% for AU, -4.55% for SPA, and -5.14% for XO. Due to these negative expected returns, in period 2, the Black-Litterman model recommended investing in a risk-free asset offering a return of 2.26%. Therefore, the mai portfolio decided to forgo stock investments in Period 2 and instead invest in assets at the risk-free rate.

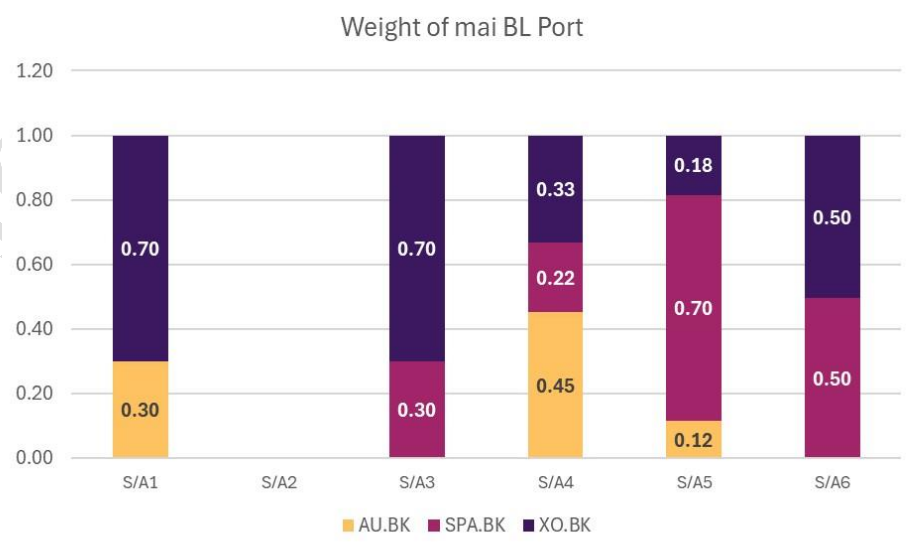

Figure 5: Weight Allocation of BL-mai Portfolio

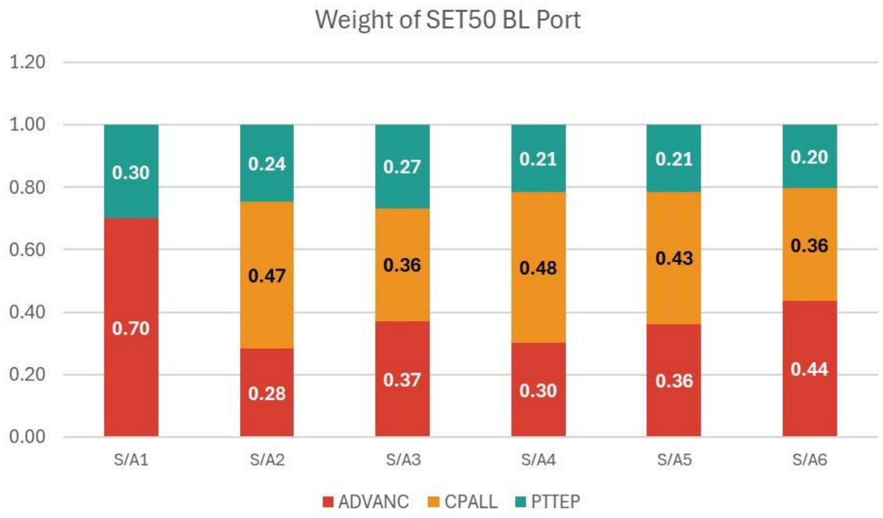

Figure 6: Weight Allocation of BL-SET50 Portfolio

Figure 6 shows that during the first investing period, CPALL stock was not included in the Black-Litterman SET50 portfolio. This decision was influenced by both the investor's perspective and the Black-Litterman model's posterior expected return. Investor view indicates a negative price movement for CPALL stock which has an impact on posterior expected return of CPALL that has lowest expected return in that period. As a result, the portfolio decided to not invest in CPALL during the first period.

4.2.2 Portfolio Value and Performance

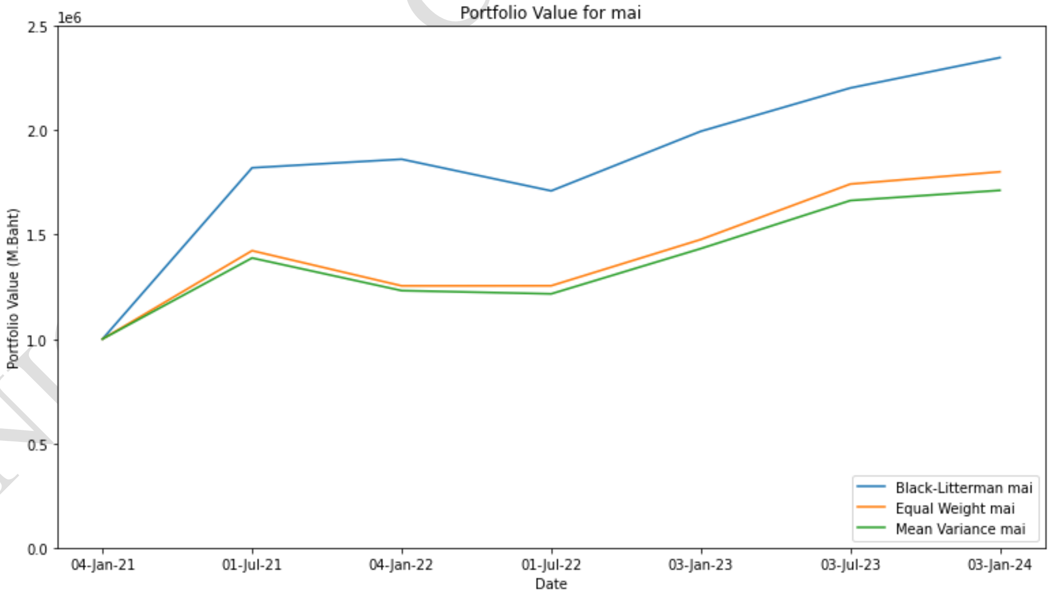

Figure 7: Mai Portfolio Value

Table 4: Mai Portfolio Performance

	Black-Litterman	Equally Weight	Mean Variance
Average Annual Return	36.62%	23.18%	21.05%
SD, Annual	41.73%	24.31%	22.78%
Sharpe Ratio	0.82	0.86	0.82

Figure 7 presents the value movements of three portfolios constructed for the mai market: BL-mai, Equal Weight-mai, and Mean Variance-mai. The overall trends of the three portfolios are generally similar, except for a significant increase in the BL-mai portfolio value on July 1, 2021. This significant increase highlights the effectiveness of the weight allocation process during the initial investment period of the BL-mai portfolio, in which the weights are specified in figure 5. A more comprehensive evaluation of portfolio performance is presented in Table 4, which summarizes key metrics including Average Annual Return, Annual Standard Deviation, and Sharpe Ratio for all three portfolios. BL-mai, with an annual return of 36.62%, outperforms the other two portfolios in terms of return. Both BL-mai and Mean Variance-mai have a Sharpe Ratio of 0.82, which is slightly lower than the Equal Weight portfolio's Sharpe Ratio of 0.86. This indicates that the Equal Weight portfolio has done the best in terms of risk-adjusted return. While BL-mai generates a strong return, it carries slightly more risk in achieving that return, as evidenced by the lower Sharpe Ratio.

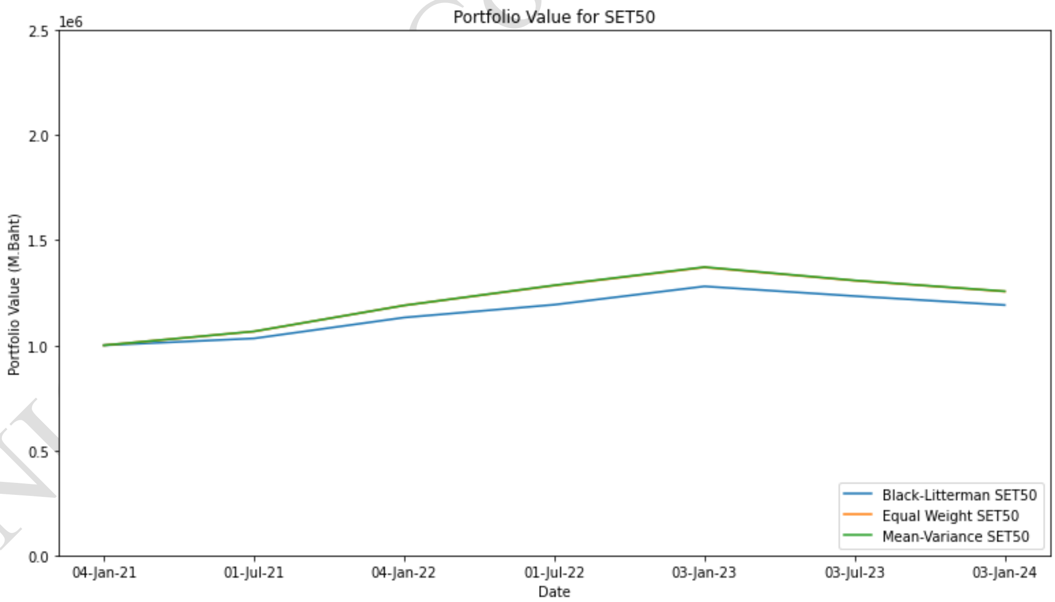

Figure 8: SET50 Portfolio Value

Table 5: SET50 Portfolio Performance

	Black-Litterman	Equally Weight	Mean Variance
Average Annual Return	6.18%	8.12%	8.15%
SD, Annual	7.16%	8.66%	8.69%
Sharpe Ratio	0.55	0.68	0.68

Figures 8 and Table 5 present the performance of the three portfolios constructed for the SET50 market: BL-SET50, Equal Weight-SET50, and Mean Variance-SET50. Unlike the mai market, the BL-SET50 model does not show any significant superiority over the other two strategies in terms of portfolio value or risk-adjusted returns. The Equal Weight-SET50 and Mean Variance-SET50 portfolios have similar value movements across all investment periods, reflected in their identical Sharpe Ratios.

When comparing portfolios in the SET50 market to those in the mai market, the research showed that SET50's portfolios have lower Sharpe ratio. This difference can be attributed to the size effect within stock markets. Smaller companies, typically represented in the mai market, tend to have higher expected returns compared to larger companies in SET50. This phenomenon, known as the size risk premium, smaller stocks offer higher expected returns to compensate investors for the increased risk associated with their lower liquidity and potentially higher volatility. As a result, portfolios invested in smaller capitalization stocks, mai's portfolio, may achieve higher returns alongside greater risk, potentially leading to a higher Sharpe Ratio.

5. Conclusion

This study explored the effectiveness of combining a Long Short-Term Memory (LSTM) deep learning approach with investor views within the Black-Litterman model for portfolio allocation. The effectiveness of this proposed model was evaluated across two distinct stock markets, mai and SET50, which have different market capitalization characteristics and market behavior. The evaluation process employed a backtesting methodology spanning three years from 2021 to 2023. Both portfolios contain an equal number of stocks selected based on market capitalization and data availability. The mai portfolio comprised stocks with smaller market capitalizations, AU, SPA, and XO. While the SET50 portfolio consisted of stocks with larger market capitalizations, ADVANC, CPALL, and PTTEP. Both portfolios' weights are adjusted every six months.

The investor views in this study were generated using an LSTM model to forecast future stock prices and calculate percentage changes. The LSTM model was trained solely on historical price data of each stock. The training dataset has been covered since the first trading day. The overall accuracy of predicted stock prices in the mai market is better than in the SET50 market. However, the forecasted prices for both markets are not as accurate as expected. Thus, this paper concludes that relying solely on historical price data is insufficient for training a model to predict stock prices accurately over a six-month horizon.

The Black-Litterman model optimized weight allocation by using a maximum Sharpe Ratio as criterion, subject to a constraint on individual stock holdings not exceeding 70% of the portfolio. The performance of the Black-Litterman model was evaluated by comparing with equal weight portfolio and mean variance portfolio. From the mai market, the BL-mai portfolio yielded the highest return among all strategies, but it also got the highest risk. While the BL-mai portfolio's Sharpe Ratio matched that of the mean variance portfolio, it remained lower than the equal weight portfolio. Conversely, in the SET50 market, the BL-SET50 portfolio did not exhibit a significant advantage over the simpler strategies. It yielded lower returns and a lower Sharpe Ratio compared to both benchmarks. The BL model performed better in the mai market, with the BL-mai portfolio achieving a higher Sharpe Ratio compared to the SET50 market. The higher Sharpe ratio in the BL-mai portfolio can indicate better performance in the stock allocation of the proposed model in mai market. Nevertheless, the performance of the BL portfolio in both markets cannot generate superior results than the simple investment strategy. This leads to the conclusion that, despite the proposed model performing moderately to a certain level, it is still insufficient and has room for improvement.

In comparison with Punyaleadtip (2022), which also examines the performance of Black-Litterman with deep learning methods with stocks in Thailand, SET100, during 2019 to 2021. Punyaleadtip, 2022, combines LSTM and SVR together to calculate investor view by using LSTM to forecast technical indicators in next 3 days, after that used the forecasted technical indicators to forecast future stock's price by SVR. Portfolio in Punyaleadtip, 2022 consist of twenty-one stocks from eleven sectors in SET100 index. The result of Punyaleadtip, 2022 found that. Black-Litterman portfolios integrating LSTM and SVR models achieved higher returns compared to the SET100 index but had greater negative maximum drawdown. The Black-Litterman portfolios of SET100 in Punyaleadtip, 2022 got an average annual return of 47.1% over 2019 to 2021. This research conducts a simpler deep learning approach in calculating investor view by using LSTM to forecast the stock price in next 6 months, which uses historical price alone to train the model. The Black-Litterman portfolio in this research consists of 3 stocks from two industries of mai and three sectors of SET50. The BL-mai and BL-SET50 in this research have an average annual return of 36.62% and 6.18% respectively over 2020 to 2023.

For further development of this study, integrating additional features beyond historical prices into the LSTM model could be explored. These features might include various market indicators, economic data, or company-specific metrics that could enhance the model's predictive capabilities. Furthermore, studying alternate deep learning architectures or integrating ensemble approaches that combine several models could lead to better performance of models.

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Long-run Evaluating the Influence of Venture Capital, Private Equity, Underwriter Reputation on IPOs Performance During Hot Market Conditions: Evidence from the Thai Market

Nopphanut Ngamvitroje[1] and Nada Chunsom[2]

Abstract

This study analyzes the long-term performance of Initial Public Offerings (IPOs) in Thailand. This is achieved by utilizing a range of methods to assess the importance of an initial public offering's excessive or insufficient performance. The study examines abnormal returns over 12, 24, and 36-month periods in relation to the closing price on the third day. It analyzes a sample of 282 firms that were listed on the Market for Alternative Investment (MAI) and the Stock Exchange of Thailand (SET) between 2009 and 2020. The study analyzes the performance of venture capital (VC) and private equity (PE) portfolios, distinguishing between those that are backed and those that are not. Additionally, it investigates how these portfolios perform in both favorable and unfavorable initial public offering (IPO) markets. The study also assesses the influence of underwriter reputation on the performance of both supported and unsupported venture capital (VC) and private equity (PE) initial public offerings (IPOs). The BHAR and CAR methods resulted in abnormal long-term returns, with the MAI outperforming the SET. Generally, venture capital and private equity investments tend to have lower performance compared to other types of investments. Unsecured venture capital and private equity investments, as well as initial public offerings (IPOs) in popular markets, typically exhibit inferior long-term performance unless they receive support from reputable underwriters. Regression analysis indicates that specific variables exhibit a restricted ability to predict outcomes over a period of time.

Keywords: Initial Public Offering, Long-term Performance, Market-Adjusted Returns, Hot Issue Market, Venture Capital, Private Equity, Underwriter Reputation

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การศึกษาผลกระทบของธุรกิจเงินร่วมลงทุน ทุนส่วนบุคคลนอกตลาด ชื่อเสียงของผู้จัดจำหน่ายหลักทรัพย์ต่อผลตอบแทนระยะยาวของหลักทรัพย์ที่เสนอขายให้แก่ประชาชนทั่วไปครั้งแรกในสภาวะตลาดร้อน: หลักฐานเชิงประจักษ์ของตลาดหลักทรัพย์ไทย

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บทคัดย่อ

วัตถุประสงค์บทความนี้คือการศึกษาประสิทธิภาพระยะยาวของการเสนอขายหลักทรัพย์แก่ประชาชนทั่วไปครั้งแรก (IPO) ในประเทศไทย โดยใช้วิธีการหลากหลายเพื่อประเมินความสำคัญของการแสดงผลที่เกินกว่ามาตรฐานหรือต่ำกว่ามาตรฐานของหลักทรัพย์ IPO จากการใช้ตัวอย่างของบริษัท 282 บริษัทที่ลงทะเบียนในตลาดหลักทรัพย์แห่งประเทศไทย (SET) และตลาดหลักทรัพย์รอง (MAI) ระหว่างปี พ.ศ. 2552 ถึง 2563 จากการศึกษาวิเคราะห์ผลตอบแทนที่ผิดปกติในช่วงเวลา 12, 24, และ 36 เดือน โดยเปรียบเทียบกับราคาปิดในวันที่สามของการซื้อขายหลักทรัพย์ นอกจากนี้การวิจัยยังศึกษาประสิทธิภาพของหลักทรัพย์ IPO ในพอร์ตโฟลิโอต่าง ๆ ภายใต้สภาวะตลาดที่แตกต่างกันระหว่างตลาดร้อนและตลาดเย็น พร้อมทั้งแยกความแตกต่างระหว่างธุรกิจเงินร่วมลงทุน (VC) และทุนส่วนบุคคลนอกตลาด (PE) ที่ได้รับการสนับสนุนและไม่ได้รับการสนับสนุน อีกทั้งยังประเมินผลกระทบของชื่อเสียงของผู้จัดจำหน่ายหลักทรัพย์ต่อผลการดำเนินงานของธุรกิจเงินร่วมลงทุน (VC) และทุนส่วนบุคคลนอกตลาด (PE) ที่ได้รับการสนับสนุนและไม่ได้รับการสนับสนุน ผลการศึกษาชี้ให้เห็นถึงผลตอบแทนที่ผิดปกติระยะยาวโดยใช้วิธีการซื้อและถือผลตอบแทนที่ผิดปกติ (BHAR) และผลตอบแทนสะสมที่ผิดปกติ (CAR) โดยที่ตลาดหลักทรัพย์รอง (MAI) มีประสิทธิภาพดีกว่า ตลาดหลักทรัพย์แห่งประเทศไทย (SET) นอกจากนี้หลักทรัพย์ IPO ที่จดทะเบียนในตลาดร้อนมีประสิทธิภาพระยะยาวที่ต่ำกว่ามาตรฐาน และบริษัทที่มีธุรกิจเงินร่วมลงทุน (VC) และทุนส่วนบุคคลนอกตลาด (PE) ที่ได้รับการสนับสนุนมีแนวโน้มที่จะแสดงผลการดำเนินงานที่ต่ำกว่ามาตรฐานเมื่อเทียบกับที่ไม่ได้รับการสนับสนุน ยกเว้น เมื่อบริษัทที่ได้รับการสนับสนุน

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จากผู้จัดจำหน่ายหลักทรัพย์ที่มีชื่อเสียงพร้อมทั้งมีการอธิบายโดยวิเคราะห์การถดถอยแสดงให้เห็นว่าตัวแปรบางตัวมีค่าพยากรณ์ที่จำกัดเมื่อเวลาผ่านไป

คำสำคัญ: หลักทรัพย์ที่เสนอขายแก่ประชาชนทั่วไปครั้งแรก, ผลตอบแทนระยะยาว, ผลตอบแทนที่ปรับตัวตามตลาด, ตลาดร้อน, ธุรกิจเงินร่วมลงทุน, ทุนส่วนบุคคลนอกตลาด, ชื่อเสียงของผู้จัดจำหน่ายหลักทรัพย์

1. Introduction

1.1) Statement of the Problems

An Initial Public Offering (IPO) is a significant event for a company where it sells its shares to the public for the first time in order to raise funds for expansion and allow existing shareholders to sell their shares (Brealey et al., 2003; Jenkinson and Ljungqvist, 2001). Generally, initial public offering (IPO) companies are relatively new and small, which means they come with inherent risks and depend heavily on their performance after going public. A significant body of literature extensively examines anomalies in the performance of initial public offerings (IPOs), specifically focusing on underperformance. This refers to the situation where IPOs generate negative returns in their initial years in comparison to the overall market. Notable studies by Ritter (1991) and Loughran and Ritter (1995) have contributed to this discussion. Researchers aim to elucidate the reasons behind this persistent underperformance when compared to different groups for an extended period of time. Key factors such as the participation of venture capitalists, private equity, and the reputation of underwriters are identified as significant influences (Ritter, 1991; Loughran and Ritter, 1995). Significantly, these factors do not operate separately, resulting in fascinating connections in the IPO landscape. For example, venture capitalists or private equity firms may collaborate with trustworthy underwriters to minimize concerns regarding the underwriting process, thereby decreasing information gaps and uncertainties regarding the actual worth of a company. On the other hand, venture-backed IPOs may involve investment bankers who are not as reputable, as the process of validation does not require prestigious underwriters. This phenomenon indicates that venture capitalists, who are seeking to establish their trustworthiness, may not be greatly influenced by the decision to engage high or low-reputation investment bankers for venture-backed initial public offerings (IPOs). Recent literature highlights that venture-backed initial public offerings (IPOs) do not demonstrate long-term underperformance, in contrast to IPOs underwritten by less reputable sources (Vithessonthi, 2008). This raises the question of whether there is a disparity in the long-term performance of venture-backed IPOs that are underwritten by investment bankers with either high or low reputation. Unfunded initial public offerings (IPOs), which rely on the reputation of underwriters for credibility, raise the question of whether reputable underwriters can reduce the risks associated with underwriting IPOs that are not supported by venture capital. The discussion also examines the periodic pattern of initial public offerings (IPOs) during periods of high and low demand. Prior research conducted by Ibbotson, Jaffe, Ritter, Lowry, and Schwert has demonstrated that volume and initial returns display periodic fluctuations. Hot issue markets are characterized by elevated volume and returns, whereas cold issue markets exhibit the opposite pattern. In markets that are experiencing high levels of activity and attention, it is more common for companies to perform below expectations, and this is often associated with the decision of riskier firms to become publicly traded. While extensive research has been conducted on these phenomena in developed markets, there is a notable lack of research in developing markets such as Thailand.

1.2) Objective and Purpose

The objective of this study is to examine the influence of venture capitalists, private equity, and the reputation of underwriters on the extended-term success of Initial Public Offerings (IPOs) in Thailand. The study seeks to utilize comprehensive performance indicators to acquire insights into the phenomena of underperformance and assess the efficiency of high-reputation underwriters in mitigating risks. In addition, the study will investigate the mechanisms of underperformance in Thailand's markets during both periods of high and low activity.

1.3) Significance of Research

Our study significantly improves the current body of knowledge by performing a thorough comparative investigation of the long-term performance of Venture Capital (VC), Private Equity (PE), Hot market and underwriter reputation in Thailand. It examines the dynamics of both popular and unpopular issue markets, offering insight into the factors that affect the success of initial public offerings (IPOs) in the Thai market. Furthermore, our contribution stands out due to its all-encompassing approach in assessing the long-term performance of IPOs. We enhance our investigation of IPO performance dynamics by utilizing an updated dataset and broadening the research to encompass the Stock Exchange of Thailand (SET) and the Market for Alternative Investment (MAI). This enables us to offer discernments that might have been overlooked by previous investigations (Sherif et al., 2016).

In our research, we use Cumulative Abnormal Return (CAR) and Buy and Hold Abnormal Return (BHAR), building on the methods of Komenkul et al. (2014) and Chorruk and Worthington (2010). Our study aims to fill gaps in the existing literature about Thai markets by looking at important factors like Venture Capital (VC), Private Equity (PE), underwriter reputation, and market conditions. We also apply regression analysis to explore the relationships between these variables and their importance for long-term performance. This approach strengthens the reliability of our findings. Our work makes a significant contribution to understanding initial public offerings (IPOs) in developing countries like Thailand, providing useful insights for both investors and policymakers.

1.4) Scope of work

This study analyzes a total of 282 Thai equities that were publicly traded. Among these, 151 stocks are listed on the Market for Alternative Investment (MAI) and 131 stocks are listed on the Stock Exchange of Thailand (SET) (Komenkul et al., 2014). We selected the timeframe for our analysis as January 1, 2009, to January 1, 2020, as it corresponded with the start of the Great Recession's recuperation and the upsurge in initial public offerings (IPOs). In addition to examining IPOs during typical periods, we have also incorporated IPOs from the COVID-19 period. This is fascinating since adverse information regarding businesses tends to spread rapidly during periods of uncertainty and can offer significant insights into their performance.

The data we used came from the official Form 69-1 prospectus filing, which is available on the SEC's IPO filing database. The SEC website (http://sec.or.th), the SET website (http://set.or.th), and SET SMART (http://www.setsmart.com) are some of the sources of information about IPO companies listed on SET and MAI between 2009 and 2021. Generally speaking, a prospectus for a company going public has to disclose a lot of information, including the company's history, structure, finances, and risks. All of these prospectuses are available on the Thai electronic database of the SEC. To put it another way, we are examining a number of Thai initial public offerings (IPOs) that occurred between 2009 and 2021, including the COVID-19 pandemic. The information we used to analyze these companies' performance during this uncertain period came from official filings and other trustworthy sources.

2. Literature review

2.1) Initial Public Offering (IPO) and IPO Underpricing

Wasserman (2010) states in "IPO Dynamics: A Comprehensive Overview" that IPOs are significant for firms due to the rigorous evaluation process they undergo before being listed on the stock market. The Stock Exchange of Thailand (SET) released a publication called "Going Public Guide" in 2013. This booklet provides comprehensive information on the specific prerequisites and the pre-IPO stage that companies are required to adhere to. Financial consultants assist in the process of corporate restructuring to ensure compliance with SET regulations. During the IPO process, the company going public and its financial advisors gather extensive information for investors in a thorough prospectus that meets the rules set by the SEC. Despite being open to the public, trading limitations are in place, particularly for executives and important stakeholders, highlighting the intricate nature of the initial public offering (IPO) market. Ever since Reilly & Hatfield introduced the concept of first-day returns in initial public offerings (IPOs) in 1969, experts have been attentively observing the phenomenon referred to as short-term underpricing. The research conducted by Ibbotson in 1975 and Rock in 1986, as reviewed by Smith in 2014, regularly demonstrates underpricing that surpasses 15 percent, accompanied by considerable positive anomalous returns. While information asymmetry and signaling theories are commonly used to explain underpricing, this study takes underpricing as an established phenomena and does not explore these specific ideas. Instead, the study focuses on analyzing the long-term performance of initial public offerings. The examination of theories formulated to elucidate the temporary outperformance (underpricing) of initial public offerings (IPOs) acts as a catalyst for several ideas that explicate long-term performance.

2.2) Hot Issue Market

This section examines the theoretical foundations that explain the behavior of initial public offerings (IPOs) in markets where there is high demand for new issues. Notable academics in this area include (Ibbotson & Jaffe, 1975) and (Ritter, 1984). In simple terms, an Initial Public Offering (IPO) that generates extremely high profits is known as a hot issue market, whereas an IPO that yields lower-than-average returns is referred to as a cool issue market. Despite significant research, the characteristics of the hot topic market remain challenging to understand. Securities with more risk are more prone to IPO underpricing due to the greater uncertainty around their underlying worth, as stated by Ritter (1984). Empirical evidence from several academics, including Lucas and McDonald (1990), Agathee et al. (2012), Loughran and Ritter (2004), Yung et al. (2008), and Peterle and Berk (2016), supports the signaling theory. This evidence indicates that in hot markets, issuers are often enterprises of higher quality. Nevertheless, a study conducted by Kooli and Suret in 2004 on Canadian IPOs revealed that despite being high-quality enterprises that went public under favorable market conditions, these IPOs had poor performance after three and five years of trading. This finding aligns with other studies on prolonged underperformance and suggests a detrimental correlation between popular markets and the long-term performance of initial public offerings (IPOs).

2.3) Private Equity and Venture Capital

The concept of private equity (PE) can be subject to several interpretations, making it challenging to ascertain the most suitable one. Private equity (PE) refers to investments in equity that are held for medium- or long-term durations and are not traded publicly (Cendrowski, 2012). In addition to its principal application of buyouts (BO) and leveraged buyouts (LBO), it also involves investments in debt funds, hedge funds, and other instruments.

Under the BO/LBO structure, a private equity firm assumes control of another company, acquires it through a purchase, and implements modifications that enhance its worth. To assess the value added by private equity, refer to the study conducted by Bergstrom et al. (2006). Based on their analysis of 1,370 non-private equity (PE)-backed and 152 PE-backed initial public offerings (IPOs) from the London Stock Exchange and Paris Stock Exchange between 1994 and 2004, it was found that PE-backed IPOs generally experience less underpricing and achieve superior long-term performance compared to non-PE-backed IPOs. Nonetheless, regardless of their main purpose, holding companies are permitted to participate in private equity operations in Thailand. When foreign funds invest in Thai companies through Special Purpose Vehicles (SPVs) established under Thai law, private equity investments frequently entail cross-border transactions. The Foreign Business Act and the Land Code, among other restrictions on foreign investment, have a significant influence on this structure in Thailand. To ensure Thai ownership of portfolio companies, SPVs, usually Thai entities, are used to ensure compliance with these restrictions. Typically, Thai private equity firms create SPVs in order to take over managerial control and purchase majority stakes in local businesses. Before selling their shares or listing on a stock exchange, SPVs usually invest for three to seven years, trying to improve or grow the companies in their portfolio (Noda et al., 2021). This claim is backed by a comparison of initial public offerings (IPOs) that have a high institutional ownership percentage—the majority of which are holding companies. The long-term performance of initial public offerings (IPO) firms is found to be considerably influenced by institutional investors, both within a year and three years. IPO firms with high institutional ownership outperform those with low institutional ownership, according to research using CRSP value-weighted and S&P 500 index adjusted Buy-and-Hold Returns (BHRs) (Doukas and Gonenc, 2000). In light of this, the research paper classifies the holding company or sizable share group that participates in Thailand initial public offerings (IPOs) under the private equity heading.

For venture capital, investments are provided to early-stage, innovative, and high-growth startup companies. Typically, these investments occur during the seed stage, offering funding to research, evaluate, and develop an initial concept before a business enters the startup phase (Cumming, 2012). Essentially, venture capital is similar to private equity, with a key difference: venture capitalists do not seek majority control, impose management strategies, or engage in turnaround operations. Instead, they invest in a company's growth, allowing founders to continue with their business strategy. Empirical research by Barry, Muscarella, Peavy, and Vetsuypens (1988) presents evidence that the IPOs of firms initially backed by venture capitalists exhibit similar levels of underpricing as those without such backing. Venture capitalists, who possess private information about the prospects of the firms they support, frequently enter the IPO market, potentially having a greater incentive to build a reputation for backing successful companies.Brav and Gompers (1997) further emphasized that both VC-backed and non-VC-backed firms tend to underperform in the first five years after going public. This underperformance can be attributed to changes in capital allocation and the cost of capital, which negatively affect overall firm performance. Additionally, Achima Chalarat (2018) highlights that Venture Capital Equity (VCE) has a negative significant effect on long-term firm performance in the context of Thai IPOs. This suggests that while VC can be beneficial during the early stages, its influence may become detrimental over time.

2.4) Underwriter Reputation

The market's general consensus is that an IPO's pricing is affected by the underwriters chosen. (Louge, 1973) argues that investors' willingness to pay for the offered shares may vary depending on whether they choose a prestigious or non-prestigious underwriter. This concept is based on the idea that, when a company goes public, investors may not fully understand the true value of its shares, and the market is informed about the firm's true value by the standing of the underwriters that were chosen. Based on (Rock et al., 1986), Carter & Manaster (1990) developed their model to investigate the possibility that IPO underpricing is influenced by the underwriter's reputation. It is argued that elite investment banks only list initial public offerings (IPOs) of low-risk companies in order to preserve their standing in the market. This gives the market a clue as to whether the IPO will be priced correctly. They found that underwriter prestige and price variance for the initial public offerings (IPOs) they manage significantly correlated negatively, indicating that IPOs from respectable investment banks are likely to be more expensive. According to (Schöber, 2008), employing esteemed underwriters certifies that the price range is more accurate. This is due to the fact that their reputation and future business-generating potential are expected to have a higher net present value than the profit from underwriting an inflated IPO and misleading investors about the IPO price, which will ultimately result in less business. According to (Michaely & Shaw, 1994), IPOs underwritten by respectable investment banks also perform better over time and encounter much less underpricing.

2.5) Uncertainty in Long-run IPO performance

The uncertainty implies that higher-quality companies, with lower levels of uncertainty, typically outperform in the long run following their IPO. In contrast to the signaling hypothesis, which uses specific indicators to identify high-quality firms, in this case, the quality is reflected through proxy variables. In a study of 254 Greek initial public offerings (IPOs), (Thomadakis et al., 2012) investigated a number of variables, including board classification, public vs. private status, firm size, ownership concentration, and underwriter reputation. However, they found only flimsy evidence for their impact on IPO performance. These variables, which also included firm size, underwriter reputation, average pre-tax profit, and total direct listing costs, were further discussed by (Goergen et al., 2007). They discovered a strong correlation between long-term performance and firm size, with pre-tax profit and listing expenses having a major explanatory power. Remarkably, long-term performance was not explained by underwriter age or reputation, despite earlier research (Ritter, 1991). Furthermore, Miller (1977 and 2000) noted that in situations where the value of a newly established company is uncertain, optimistic investors may overestimate its worth relative to more cautious ones. Miller proposed that the degree to which people's opinions diverge regarding the IPO will determine its long-term success. The prices of the company's shares are anticipated to decline as time goes on and people's knowledge base grows more homogeneous. This difference in views is anticipated to be even more pronounced in the event that the initial valuation of the IPO remains uncertain. Therefore, the theory is that the company's performance following its IPO will most likely be worse if there is a lot of uncertainty prior to it. They took into account four factors—the company's age, the size of the IPO, the industry it operates in, and the company's financial strength—that could indicate how uneasy people were before a company went public in order to determine whether their hypothesis was correct. Researchers found that the least successful companies were those that were relatively new, had low sales, were not well-known, had few institutional investors, were erratic, had a high initial stock price, were listed on smaller stock exchanges, and belonged to specific industries.

2.6) Previous long-run performance studies on the of IPOs

The frequency of IPO underpricing and short-term outperformance has been shown by numerous international studies, but the long-term dynamics of IPOs continue to be mysterious. A seminal study (Ritter, 1991) examined US market data and found a sustained -23.4% three-year underperformance in market-adjusted buy-and-hold returns. Ritter used alternative benchmark portfolios to investigate potential measurement issues, looking at things like gross proceeds, initial returns, industry categorization, year of issue, and firm age. A more recent study found that long-term underperformance is a phenomenon that transcends national boundaries and industry. (Kooli and Suret, 2004) examined 445 Canadian initial public offerings (IPOs) from 1991 to 1998 and found that there was a notable underperformance during the five years following the IPO. Underperformance's importance, however, varies according to the methodology and weighting system used. A study conducted in China by Cai et al. (2008) on A-shares listed on the Shanghai Stock Exchange revealed a performance underperformance of roughly 30% over a three-year period. In a comparable way, (Keloharju, 1993) discovered significant underperformance in Finland from 1984 to 1989, especially among smaller IPO companies.The long-term performance of initial public offerings (IPOs) was first examined in the context of Thailand by Allen et al. (1999). From 1985 to 1992, 151 initial public offerings (IPOs) were listed on the Stock Exchange of Thailand's (SET) main board. (Komenkul et al., 2014) (Sherif, 2012). A non-statistically significant long-run abnormal return of 10.02% was discovered by Allen et al. (1999) using the equally-weighted cumulative market-adjusted return (CAR) in the 36th month following listing (Komenkul et al., 2014). Remarkably, this return went up when an IPO value-weighted portfolio was taken into account. On the other hand, when measured by equally-weighted cumulative and buy-and-hold abnormal returns, Thai IPOs underperformed in comparison to the market at the end of a 3-year post-listing period (Komenkul et al., 2014) (Chorruk and Worthington 2010). (Komenkul et al., 2014). Furthermore, the long-term performance is compared with industry groups and market indices by (Chaiwut, 2019). The study covers 298 companies' initial public offerings (IPOs) that were listed between 2003 and 2018 on the Market for Alternative Investment (MAI) and the Stock Exchange of Thailand (SET). The study looks into abnormal long-term returns over a 60-month period using data from SETTRADE and SETSMART. It uses a number of measures, including Buy and Hold Abnormal Return (BHAR), Cumulative Abnormal Return (CAR), and Abnormal Return (AR). The results show that there are no statistically significant abnormal long-term returns on average, but they do show that IPO securities in the SET100 Portfolio have abnormal returns that exceed the market, showing a statistically significant but declining trend.

3) Methodology

3.1) Research design

2.1 Black-Litterman Model

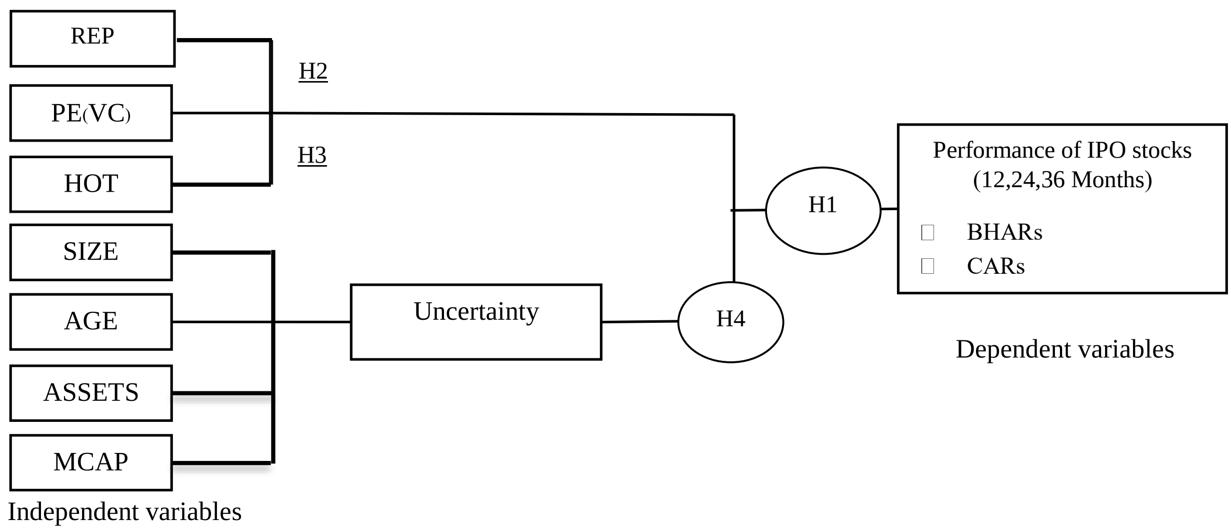

Figure 1: Conceptual Framework

In research, people typically focus on stock returns to evaluate market performance. While some researchers explore alternative methods, such as accounting, to evaluate a company's long-term performance post-IPO (Ritter, 1991; Brav et al., 2000), most consider stock returns more reliable as they reflect investors' future expectations, unlike accounting methods that rely on historical data. This study follows the precedent set by others and concentrates on stock returns, excluding accounting methods. In this study, the SET and MAI Indices serve as the benchmarks against which raw returns are analyzed. We compute monthly abnormal returns over three timeframes: 12, 24, and 36 months following the IPO. Using an event-time methodology, we investigate the long-term performance of Thai initial public offerings (IPOs) in both primary and secondary markets, employing both abnormal return measures, CARs and BHARs. Our analysis is divided into two sections: the first examines Hot Market issues involving both Backed VC/PE and Non-Backed VC/PE, while the second contrasts these two categories with respect to underwriter reputation. Each categorized portfolio is structured for statistical analysis, serving as a variable in models to evaluate and compare the relative significance of various portfolios, with a fixed uncertainty variable across all. This approach allows us to identify the significance of factors influencing long-term performance, which will be explained through four hypotheses in the hypotheses section (Figure 1). When discussing the long-term performance of IPOs, it usually refers to the three years after they start trading. For clarity, one year is defined as 252 business days and one month as 21 consecutive trading days. The study aims to assess how well IPOs perform over an extended period, excluding initial stock returns influenced by underpricing.

Year(s)	Months	Trading Days
1	12	252
2	24	504
3	36	756

Figure 2: Time window working with long-run performance of IPOs adapted from "Long-term IPO performance: A Scandinavian event-time study." by Poulsen, M. M., and Breuner Nielsen, P. R., 2017.

The first two trading days are eliminated in order to accomplish this, with the difference between the second and third day serving as the first measure. Scholars differ in how they define the first return period. For example, Ritter (1991) looks at the first day, whereas Kooli and Suret (2004) use five days. Like this study, the majority exclude the first day in order to account for underpricing. In order to reduce biases from the second day, the first three observations are omitted in accordance with recent studies. Because of this adjustment, there are 19 trading days in the first month and 21 in the following months. As in previous research, daily data is utilized to calculate monthly returns (Ritter, 1991). Various techniques are used in current empirical research to investigate the long-term performance of initial public offerings (IPOs) (Komenkul et al., 2014).

3.2) Hypotheses

To explore our research question, we examined existing studies and created a conceptual framework (Figure 1) to generate ideas for answering our questions. We also gathered information from these studies to test our hypotheses.

Most previous research consistently shows that IPOs tend to perform poorly in the long run.

Hypothesis 1: Do All firms will experience underperformance in the long run

Also, (Chaiwut, 2019) and (Komenkul, 2015) show that the secondary market, particularly smaller capitalized companies listed on the MAI index, experience lower underperformance in the long run compared to the main index market, SET.

Hypothesis 1.1: Do secondary market experience lower underperformance in the long run?

Additionally, IPOs with VC/PE support or guided by High Reputation Underwriters tend to perform better than non-backed IPOs and those linked to Low Reputation Firms. So, our second hypothesis will explore this (Doukas and Gonenc, 2000).

Hypothesis 2: Do Backed VC/PE and High Reputation Underwriters will perform better than others in the long run

Past studies show that companies doing IPOs in a hot market tend to do worse than those in a cold market.

Hypothesis 3: All firms will underperformance more than others when the firm is listed in a hot issue market

Less uncertainty is associated with better-quality firms, leading to strong long-term performance after going public. (Ritter's, 1991) (Miller 1977 and 2000)

Hypothesis 4: A high-quality firm will be associated with less uncertainty and better long-term performance. These variables, including asset value, age, size of the IPO offer, and Market Cap at Offer, are positively related to long-term performance.

3.3) Research tools

3.3.1) Definitions of Hot and Cold Markets

Based on monthly IPO volumes, we identify hot and cold markets using the methodology described by Alti (2006). How to do it is as follows: First, to account for seasonal variations in the monthly number of IPOs, we smooth the data using a three-month moving average. These monthly averages are then divided into High and Low categories. Higher averages are found in the hot months and lower averages in the cold months. This approach is consistent with the definition of hot and cold months given by Alti (2006), according to which hot months in the moving average distribution are above the median and cold months are below it.

3.3.2) Value Weight

Furthermore, by building a historical value-weighted portfolio based on the firm's size at the time of going public, we hope to assess our hypothesis. We created value-weighted portfolios for various categories in light of the sample size variations across definitions. We justify this by comparing the long-term performance of a portfolio consisting of the biggest companies at IPO to a portfolio that is equally weighted. This computation's weights will be determined by:

$$VW_i = \frac{V_i}{\sum V_i}$$

where V_i *is the market capitalization at offer for company*$_i$

Three different time periods will be evaluated in my research: 12 24, and 36 months. As recommended by Bergström et al. (2006), a longer period facilitates the identification of performance patterns and the detection of abnormal performance. A shorter 12-month horizon, on the other hand, makes it possible to investigate the profitability of short-term ownership of freshly listed IPO stocks. For long-term analysis, prior research suggests using cumulative abnormal returns (CARs) and buy-and-hold abnormal returns (BHARs). Though multi-period compounding can lead to extreme values for BHARs, which raises questions about statistical robustness, they do provide insights into the experience of a buy-and-hold investor. Because of their better-understood distributional properties, some academics support CARs; however, they can show upward bias, especially when there is a bid-ask spread (Schöber, 2008).

3.3.3) Cumulative Abnormal Return (CAR)

The calculation of market-adjusted abnormal returns for company$_i$ until month t ($AR_{i,T}$) is conducted for each event month t using the following method:

$$AR_{i,T} = \left(R_{i,t} - R_{b,t}\right)$$

where $R_{i,t} = \left(P_{i,t} - P_{i,t-1}\right)/P_{i,t-1}$ *where* $P_{i,t}$ *is the last traded price of the company* y_i *in event month* t *and* $P_{i,t-1}$ *is the last traded price of the company in event month* $t - 1$. $R_{b,t}$ *is the return on the market index (SET or MAI indices) in event month* t *and is calculated as* $R_{b,t} = \left(P_{b,t}P_{b,t-l}\right)/P_{b,t-l}$ *where* $P_{b,t}$ *is the last closed stock market index in event month* t *and* $P_{b,t-l}$ *is the last closed market index in event month* $t - 1$. *and* T *is the holding period.* T *will contain 12 months, 24 months or 36 months (Sherif, 2012).*

The definition of the average market-adjusted return for a sample comprising n companies in event month t is as follows:

$$\overline{AR}_{i,T} = \frac{1}{n}\sum_{t=1}^{n} AR_{i,T}$$

Hence, the cumulative average abnormal return of company i from event month 1 to event month T is specified as follows:

$$CAR_{i,T} = \sum_{t=1}^{T} \overline{AR}_{i,T}$$

3.3.4) Buy-and-Hold Abnormal Return (BHAR)

In addition, by using the monthly buy-and-hold abnormal returns (BHARs) methodology based on the work of (Schöber, 2008), which is determined by the difference between the compounded return of the company's stock and the compounded return of the corresponding benchmark, the study seeks to investigate abnormal returns for investors who buy shares at the offering price.

$$BHAR_{i,T} = \prod_{t=1}^{T} \left(1 + R_{i,t}\right) - \prod_{t=1}^{T} \left(1 + R_{b,t}\right)$$

where $R_{i,t}$ is the stock return of company y_i in month t, $R_{b,t}$ is the return of benchmark in month t, and T is the holding period. T will contain 12 months, 24 months or 36 months.

Also, for equally-weighted (EW) portfolios, it is considered.

$$BHAR_{i,T} = \sum_{t=1}^{n} \frac{1}{n} BHAR_{i,T}$$

While, value weighted measure to calculate abnormal returns when the portfolio is weighted by the size of the companies when going public:

$$BHAR_{i,T}^{VW} = BHAR_{i,T} * VW_i$$

where $BHAR_{i,T}$ is companyi $BHAR$ at time period T, and VW_i is the corresponding company value weight.

$$CAR_{i,T}^{VW} = CAR_{i,T} * VW_i$$

where $CAR_{i,T}$ is companyi CAR at time period T, and VW_i is the corresponding company value weight.

3.4) Regression Models

Explanatory Variable	Variable name	Expected Sign
Top 3 underwriters with the highest market share are equal to 1 and 0 otherwise (dummy variable)	**REP**	(+)
Represent the PE and VC backed during the sample period. 1 Backed & 0 Non-Backed (dummy variable)	**PE(VC)**	(+)
If the firm listed in Hot market, 1 Hot & 0 Cold (dummy variable)	**Hot**	(-)
The offer size of IPO firm	**OFFERSIZE**	(+)
Age of the IPO firm measured as the number of years between incorporation and pricing date	**AGE**	(+)
Defined in this study as total assets of company at the issue year. It is relevant to the prior research, size of the issue firm	**ASSET**	(+)
Market capitalization at the issue years is also relevant to the issue size of the firm.	**MCAP**	(+)

When running a regression on performance. We do different regressions for each measurement, BHAR and CAR, where our dependent variable (Y) is as follows:

$$BHAR_t = \beta_0 + \beta_1 REP_{DUM} + \beta_2 PE(VC)_{DUM} + \beta_3 HOTMARKET_{DUM} + \beta_4 OFFERSIZE + \beta_5 AGE + \beta_6 ASSET + \beta_7 MCAP + \varepsilon_t$$

$$CAR_t = \beta_0 + \beta_1 REP_{DUM} + \beta_2 PE(VC)_{DUM} + \beta_3 HOTMARKET_{DUM} + \beta_4 OFFERSIZE + \beta_5 AGE + \beta_6 ASSET + \beta_7 MCAP + \varepsilon_t$$

$where\ t\ is\ is\ either\ 12\ month, 24\ month\ or\ 36\ month\ BHAR\ or\ CAR\ returns$

3.5) Data collection

This section provides an in-depth analysis of the data collection procedure, elucidating the standards by which IPO companies and their benchmarks were chosen. First, we followed the guidelines provided by Komenkul (2015) for selecting IPO companies. This process comprised gathering data on companies that had completed an IPO and were listed on the SET and MAI between 2009 and 2020. For initial public offerings (IPOs) on the Main Board of the Stock Exchange of Thailand, the SET index was used as a benchmark; for companies listed on the Market for Alternative Investment (the sub-market), the Second Board Index was employed. All stocks quoted on the small- and medium-sized market are included in the MAI index, and market capitalization is used to determine the weights for both the SET and MAI indices (Komenkul, 2015). Through prospectus files, the SEC (Thailand) database provided the lists of IPO companies. To confirm that the IPOs were being actively traded on the exchange, these lists were then cross-referenced with the SET database in the 'New Listed Company Information' section. All IPOs that have taken place in Thailand since 2009 are covered in this report. The IPO companies had to fulfill the following requirements in order to be included in the final sample: (i) an offer price of at least Baht 0.5 per share; (ii) an equity-only offering; (iii) the company had to be listed on either the MAI (small- and medium-sized market) or the SET (main market); (iv) price data had to be available on the DataStream database; and, last but not least, (v) companies that were classified as trusts, closed-end funds, or in the Exchange Traded Fund (ETF) sectors were excluded.

3.6) Individual IPO company stock returns and characteristic

The DataStream database provides stock price information, including closing prices on the first and third trading days, for individual initial public offerings (IPOs). The change from the second to the third day is the initial measure, and the first two days are ignored. The first three observations are omitted in order to reduce biases, and the subsequent 36-month stock returns following public offering are examined. Stock market indices like the SET and MAI indices are used to compare monthly returns. Data regarding initial public offerings (IPOs) is obtained from official prospectus filing forms (Form 69-1), which can be accessed via the Securities and Exchange Commission (SEC) of Thailand's IPO filing database (Komenkul et al., 2014). Prospectus filings and a number of other sources, such as the SEC Thailand database, SET database, and SETSMART, are used to gather information on the firm's performance, ownership structure, age, and issue amount (Komenkul, 2015).

4) Results

4.1) Descriptive statistics

Table 1: Sample size of Thai IPOs

The size of the sample broken down by exchange and the year of IPO offering.						
Year	Stock Exchange of Thailand (SET)		Market for Alternative Investment (MAI)		Total	
	Number	Percent	Number	Percent	Number	Percent
2009	6	4.6%	11	7.3%	17	6.0%
2010	4	3.1%	6	4.0%	10	3.5%
2011	3	2.3%	7	4.6%	10	3.5%
2012	8	6.1%	10	6.6%	18	6.4%
2013	11	8.4%	15	9.9%	26	9.2%
2014	16	12.2%	19	12.6%	35	12.4%
2015	20	15.3%	13	8.6%	33	11.7%
2016	10	7.6%	13	8.6%	23	8.2%
2017	21	16.0%	17	11.3%	38	13.5%
2018	7	5.3%	11	7.3%	18	6.4%
2019	11	8.4%	17	11.3%	28	9.9%
2020	14	10.7%	12	7.9%	26	9.2%
Total	131	100.0%	151	100.0%	282	100.0%

Note. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

The appropriate research approach and methodology, including sample collection and index creation for the study, were covered in the previous section. Here are the results of the data and statistical analysis presented in this section. This section of the research examines 282 common stocks that were listed on Thai stock exchanges between 2009 and 2020. Based on the year the stock was introduced, Table 1 presents the key information about the data, both collectively and specifically for the SET and MAI markets. The SET market accounted for about 65% of the newly listed stocks, while the MAI market listed 35%. Compared to previous studies on Thai initial public offerings (IPOs), such as those conducted by Korruk and Worthington (2010) with 136 IPOs and Komenkul (2015) with 227 IPOs (Sherif, 2012), this study has a larger sample size and is more recent.

Table 2: Displays how Thai IPOs listed from 2009 to 2020 performed compared to SET and MAI benchmarks, along with a normality test.

$Month_t$	N_t	Average market-adjusted returns (AR_t) (%)							
		Mean	Median	Minimum	Maximum	S.D.	Kurtosis	Skewness	Jarque-Bera
12	282	-0.0012	-0.0019	-0.0725	0.0769	0.021	2.196	0.464	63.59***
24	282	0.0006	-0.0010	-0.1030	0.1460	0.027	6.101	1.040	469.27***
36	282	0.0015	-0.0013	-0.0651	0.1467	0.023	10.355	1.977	1392.53***

Note: This table provides information on the behavior of the market-adjusted returns, excluding the initial return (IPO underpricing), for a period of up to 36 months following a company's listing or going public. The distributions' normality is confirmed by the Jarque-Bera test. Statistical significance is indicated at the 1%, 5%, and 10% levels, respectively, by symbols like ***, **, and *. Reproduced from Komenkul, K. (2015) "Under-pricing and long-run performance of Initial Public Offerings in developing markets: the case of Thailand."

We start a robustness analysis in this section to ensure the validity of our results. Thai IPOs produced excess returns for the 36 months that followed their IPOs; Table 2.3 provides the details. When working with relatively small samples, non-normally distributed excess returns can arise during the analysis of anomalous returns. The Jarque-Bera test was used to determine whether or not our data were normal. As evidenced by the statistical significance of the Jarque-Bera test, our data actually lacks normal distribution. The average market-adjusted returns (ARs) between months 1 and 36 exhibit an unequal distribution, according to research by Brown and Warner from 1980. This may affect the statistical judgments we make. Furthermore, in order to ensure the accuracy of our long-term abnormal return computations using CAR and BHAR measures, we employed a bootstrapped skewness-adjusted t-statistic. Additionally, we compared our t-statistic test with the test's significance level by comparing medians using the Wilcoxon Signed Rank Test, a method that Chaiwut, 2019 also employed.

4.2) Empirical Findings

4.2.1) Long-term Performance of Thai IPOs

Table 3 uses CAR and BHAR measures to calculate the abnormal returns of 282 IPO firms over a 36-month period following their listing. A bootstrapped adjusted t-test and the non-parametric Wilcoxon signed rank test were also used to investigate negative abnormal returns from year 1 to year 3. Interestingly, the underperformance revealed by Chorruk and Worthington (2010), who reported a three-year BHAR of -25.39% for Thai IPOs, is substantially less than that of our study using EWCAR and EWBHAR. With regard to the MAI market, small- and medium-sized IPOs, the three-year EWCAR is 53.20% (t-stat = 2.44) and the EWBHAR is 16.9% (t-stat = 1.9). At the 5% and 10% levels, statistical significance is noted. Over the long horizon period, equally weighted CARs continuously show positive abnormal performance. Over the three years following listing, all CAR samples exhibit improved performance; after month 24, the MAI CAR outperforms all other samples and the SET benchmark. Due to the Market Capitalization Effect, equally weighted and value-weighted market-adjusted CARs show comparable trends throughout event months. Mean BHARs show patterns that are similar to those of CARs; however, in the equally weighted abnormal return from months 12 to 36, all samples perform worse than CARs. Value weight, on the other hand, shows significant outperformance for all samples, with MAI outperforming the benchmark by the greatest amount during month 36. With a significance level of 0.01%, the mean BHAR for the MAI sample in year three is 92.62% (t-stat = 2.98). The 36 months that follow the IPO are marked by a steady increase in VW's BHAR for the SET market IPOs. Long-term abnormal return analysis of initial public offerings (IPOs) in the SET and MAI markets reveals that SET exhibits lower returns with EWCARs and VWCARs than MAI, but higher returns with VWBHARs, indicating that size has a greater influence on SET's abnormal returns.

Table 3: Displays the cumulative market-adjusted returns and buy-and-hold abnormal returns for Thai IPOs listed between 2009 and 2020, both equally and value-weighted.

Panel A: Equally and value-weighted cumulative market-adjusted returns																		
Equally-Weighted Cumulative Abnormal Returns (EWCARs)																		
Months	Entire sample						SET Sample						MAI Sample					
	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %
12	282	0.118	2.8***	3.02***	-1.76*	51.77%	131	0.2264	3.01***	3.02***	-1.01	42.75%	151	0.0243	0.56	-0.26	-1.14	59.60%
24	282	0.349	2.93***	2.98***	-1.59	48.23%	131	0.4537	3.02***	2.98***	-1.13	47.33%	151	0.2588	1.38	1.62	-0.93	49.01%
36	282	0.468	3.43***	3.98***	-0.51	41.49%	131	0.3939	2.44**	1.73*	-0.42	44.27%	151	0.5320	2.44**	2.98***	-0.60	39.07%
Value-Weighted Cumulative Abnormal Returns (VWCARs)																		
Months	Entire sample						SET Sample						MAI Sample					
	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	CAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %
12	282	0.2914	4.94***	4.79***	-3.15***	51.77%	131	0.2975	4.00***	4.64***	-2.8***	42.75%	151	0.2760	3.28***	3.62***	-1.66*	59.60%
24	282	0.4613	5.38***	5.47***	-3.27***	48.23%	131	0.4517	4.23***	4.04***	-2.72***	47.33%	151	0.4845	3.61***	3.62***	-2.19**	49.01%
36	282	0.6084	5.83***	6.18***	-2.9***	41.49%	131	0.5144	4.08***	3.6***	-1.71*	44.27%	151	0.8259	4.46***	4.69***	-2.09**	39.07%
Panel B: Equally and value-weighted buy-and-hold abnormal returns																		
Equally-Weighted Buy-and-Hold Abnormal Returns (EWBHARs)																		
Months	Entire sample						SET Sample						MAI Sample					
	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %
12	282	0.1187	2.85***	3.26***	-2.63***	59.57%	131	0.2160	3.4***	3.58***	-2.14**	50.38%	151	0.0343	0.63	1.22	-1.38	67.55%
24	282	0.1072	2.2**	2.69***	-2.95***	61.70%	131	0.2079	2.72***	2.53**	-2.48**	57.25%	151	0.0199	0.32	-0.13	-2.21**	65.56%
36	282	0.1744	2.68***	2.87***	-1.92*	60.28%	131	0.1807	1.88*	2.08**	-1.18	58.78%	151	0.1690	1.9*	2.24**	-1.76*	61.59%
Value-Weighted Cumulative Abnormal Returns (VWBHARs)																		
Months	Entire sample						SET Sample						MAI Sample					
	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %	N	BHAR	t-stat	Adj. t stat	s-stat	Obs <0.0 %
12	282	0.3554	4.03***	4.17***	-2.74***	59.57%	131	0.3568	3.16***	3.18***	-2.92***	50.38%	151	0.3516	2.89***	2.78***	-1.07	67.55%
24	282	0.5178	4.25***	4.09***	-2.47**	61.70%	131	0.4987	3.41***	3.46***	-2.41**	57.25%	151	0.5645	2.54**	3.08***	-1.8*	65.56%
36	282	0.6810	4.25***	4.56***	-2.47**	61.70%	131	0.5750	3.02***	2.86***	-1.74*	58.78%	151	0.9262	2.98***	3.39***	-1.84*	61.59%

Note: After 36 months of listing, the table shows the equally and value-weighted CARs and BHARs, but not the initial return. The bootstrapped skewness-adjusted t-statistics (Adj. t-stat) and conventional t-statistics (t-stat) represent the two-tailed test results of the null hypothesis, which show equality to zero. The null hypothesis is examined using the non-parametric Wilcoxon Signed Rank test (s-stat), which posits that the median abnormal return is equal to zero. The symbols ***, **, and * stand for statistical significance levels at the 1%, 5%, and 10% levels, respectively. This has to do with Thai IPOs' Long-Term Performance. Reproduced from Komenkul, K. (2015) "Under-pricing and long-run performance of Initial Public Offerings in developing markets: the case of Thailand."

4.2.2) Long-term Performance of Thai IPOs, VC, PE, and Hot Issue Market

We use cumulative abnormal returns (CAR) to analyze our IPO portfolio's long-term performance, with a focus on hot market conditions. Table 4 shows the median differences from zero for CARs over 12, 24, and 36 months in various market phases as determined by Wilcoxon tests. With the exception of Backed VC&PE, performances in the 12-month CARs are noticeably better in cold markets. In 12-month value-weighted analyses, all portfolios perform better than average, with notable gains in cold markets for All Firms, Backed PE & VC, and Non-Backed PE & VC. The examination of 24-month CARs reveals positive returns in every category, with All Firms and Non-Backed PE & VC exhibiting noteworthy value-weighted returns, signifying their superior performance. In cold markets over a 36-month period, All Firms and Non-Backed PE & VC perform better than Backed PE & VC, with one exception. Significant returns are seen for All Firms at the 5% and 10% levels in hot markets, and for Non-Backed PE & VC at the 10% level in cold markets. Hot Market Issue All Firms exhibit positive 12-month returns using buy-and-hold abnormal returns (BHAR) over 12-, 24-, and 36-month periods. Outstanding performance is shown in Backed PE & VC at 43.3%, and Non-Backed PE & VC at 24.1% and 63.29% in equal and value weights, respectively. All times, Non-Backed VC performs better than Backed VC. The results of BHAR and CAR diverge greatly. While BHAR exhibits better performance but a less significant s-statistic, CAR displays a lower positive performance but a higher significance. Given its consideration of the compound effect—a critical factor in long-term returns—BHAR may be more appropriate over extended time horizons. In comparison to Cold Markets, Tables 4 and 5 show that Hot Markets perform worse which align with (Kooli and Suret in 2004). Tables 4 and 5 illustrate the distinctions between Backed and Non-Backed VC & PE with respect to CAR and BHAR; the Backed VC & PE demonstrates the highest performance in the 24-month BHAR. Overall performance of Non-Backed VC & PE is superior, consistent with research by Achima Chalarat (2018). Therefore, we disprove the claim that, over all time periods, Backed VC & PE performs better than Non-Backed VC & PE.

Table 4: 12 months, 24 months and 36 months CARs returns by IPOs VC & PE and Hot market activity

		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %
Panel A: The entire, hot and cold returns of 12 months																
Hot issue market	Equal weighted	202	0.080	2.10**	-1.44	51.98%	70	0.185	2.57**	-0.11	40.00%	132	0.025	0.57	-0.82	58.33%
	Value weighted	202	0.269	4.07***	2.60***	51.98%	70	0.350	3.11***	-2.12**	40.00%	132	0.186	2.89***	-1.22	58.33%
Cold issue market	Equal weighted	80	0.214	1.88*	-1.12	51.25%	24	0.092	0.77	-0.57	50.00%	56	0.266	1.72*	-0.92	51.79%
	Value weighted	80	0.351	2.76***	1.67*	51.25%	24	0.120	0.93	-0.83	50.00%	56	0.518	2.59***	-1.22	51.79%
Panel B: The entire, hot and cold returns of 24 months																
		N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %
Hot issue market	Equal weighted	202	0.368	2.30**	-0.46	48.51%	70	0.675	1.62	-0.61	42.86%	132	0.704	1.78*	-0.69	51.52%
	Value weighted	202	0.406	4.52***	-2.51**	48.51%	70	0.405	2.75***	-1.46	42.86%	132	0.469	3.94***	-1.91*	51.52%
Cold issue market	Equal weighted	80	0.302	2.44**	-1.39	47.50%	24	0.181	1.34	-0.63	50.00%	56	0.354	2.11**	-1.11	46.43%
	Value weighted	80	0.594	3.00***	-2.12**	47.50%	24	0.418	1.56	-0.73	50.00%	56	0.717	2.51**	-2.10**	46.43%
Panel C: The entire, hot and cold returns of 36 months																
		N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %	N	CAR	t-stat	s-stat	Obs <0.0 %
Hot issue market	Equal weighted	202	0.514	2.79***	-0.06	43.07%	70	0.186	1.55	-0.06	38.57%	132	0.034	2.63***	-0.49	45.45%
	Value weighted	202	0.590	4.70***	-2.2**	43.07%	70	0.433	2.58**	-1.00	38.57%	132	0.228	4.03***	-1.83*	45.45%
Cold issue market	Equal weighted	80	0.351	2.68***	-0.30	37.50%	24	0.170	1.10	-0.43	37.50%	56	0.429	2.45**	-0.24	37.50%
	Value weighted	80	0.651	3.42***	-1.69*	37.50%	24	0.540	1.9*	-0.63	37.50%	56	0.727	2.77***	-1.43	37.50%

Note. The table illustrates the equally and value-weighted CARs over 36 months post-listing, excluding the initial return. The conventional t-statistics (t-stat). The non-parametric Wilcoxon Signed Rank test (s-stat) is utilized to examine the null hypothesis, suggesting that the median abnormal return equals zero. Statistical significance levels are represented by ***, **, and *, denoting significance at the 1%, 5%, and 10% levels, respectively. This addresses the long-term performance of initial public offerings (IPOs) in Thailand, especially those associated with venture capital (VC) and private equity (PE), alongside the hot issue market. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

Table 5: 12 months, 24 months and 36 months BARs returns by IPO by IPOs VC & PE and Hot market activity

Panel A: The entire, hot and cold returns of 12 months

		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
Hot issue market	Equal weighted	202	0.086	1.92*	-2.35**	58.91%	70	0.186	2.33**	-0.67	45.71%	132	0.034	0.62	-1.51	65.91%
	Value weighted	202	0.332	3.42***	-2.32**	58.91%	70	0.433	2.58***	-1.49	45.71%	132	0.228	2.46**	-1.10	65.91%
Cold issue market	Equal weighted	80	0.200	2.15**	-1.31	61.25%	24	0.105	0.86	-0.81	58.33%	56	0.241	1.96**	-0.91	62.50%
	Value weighted	80	0.418	2.06**	-1.45	61.25%	24	0.124	0.95	-0.63	58.33%	56	0.629	1.86*	-1.08	62.50%

Panel B: The entire, hot and cold returns of 24 months

		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
Hot issue market	Equal weighted	202	0.080	1.44	-2.48**	61.39%	70	0.106	1.28	-1.84*	57.14%	132	0.066	0.90	-1.87*	63.64%
	Value weighted	202	0.424	3.48***	-2.08**	61.39%	70	0.445	2.31**	-1.54	57.14%	132	0.403	2.64***	-1.63	63.64%
Cold issue market	Equal weighted	80	0.176	1.77*	-1.41	62.50%	24	0.198	0.94	-0.39	70.83%	56	0.166	1.49	-1.41	58.93%
	Value weighted	80	0.741	2.5**	-1.30	62.50%	24	0.671	1.39	-0.36	70.83%	56	0.790	2.03**	-1.58	58.93%

Panel C: The entire, hot and cold returns of 36 months

		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
Hot issue market	Equal weighted	202	0.165	2.15**	-1.68*	61.39%	70	0.128	1.23	-0.87	55.71%	132	0.184	1.77*	-1.44	64.39%
	Value weighted	202	0.633	3.43***	-1.85*	61.39%	70	0.537	2.1**	-1.26	55.71%	132	0.725	2.68***	-1.54	64.39%
Cold issue market	Equal weighted	80	0.199	1.59	-1.08	57.50%	24	0.178	0.79	-0.50	66.67%	56	0.209	1.36	-1.10	53.57%
	Value weighted	80	0.796	2.38**	-1.10	57.50%	24	0.811	1.52	-0.70	66.67%	56	0.785	1.74*	-1.23	53.57%

Note. The table illustrates the equally and value-weighted CARs over 36 months post-listing, excluding the initial return. The conventional t-statistics (t-stat). The non-parametric Wilcoxon Signed Rank test (s-stat) is utilized to examine the null hypothesis, suggesting that the median abnormal return equals zero. Statistical significance levels are represented by ***, **, and *, denoting significance at the 1%, 5%, and 10% levels, respectively. This addresses the long-term performance of initial public offerings (IPOs) in Thailand, especially those associated with venture capital (VC) and private equity (PE), alongside the hot issue market. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

4.2.3) Long-term Performance of Thai IPOs, VC and PE, and Underwriter

Table 6: Analyzes CARs returns of Thai IPOs by underwriters and backed & non-backed VC/PE over 12, 24, and 36 months.

Panel A: The returns of underwriters, both high reputation and low reputation of 12 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.126	2.10**	-1.23	50.00%	25	0.253	2.43**	-0.26	36.00%	57	0.071	0.97	-1.20	56.14%
	Value weighted	82	0.341	3.24***	-2.29**	50.00%	25	0.367	2.39**	-0.96	36.00%	57	0.324	2.22**	-1.62	56.14%
LOWREP	Equal weighted	200	0.115	2.11**	-1.29	52.50%	69	0.128	1.71*	-0.34	44.93%	131	0.108	1.47	-1.00	56.49%
	Value weighted	200	0.263	3.72***	-2.28**	52.50%	69	0.263	2.31**	-1.32	44.93%	131	0.263	3.3***	-1.65*	56.49%
Panel B: The returns of underwriters, both high reputation and low reputation of 24 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.359	2.25**	-0.44	42.68%	25	0.694	1.50	-0.98	36.00%	57	0.212	1.80*	-0.45	45.61%
	Value weighted	82	0.553	3.8***	-1.94*	42.68%	25	0.627	2.58***	-1.65*	36.00%	57	0.491	2.88***	-1.63	45.61%
LOWREP	Equal weighted	200	0.345	2.2**	-1.40	50.50%	69	0.497	1.23	-1.19	47.83%	131	0.266	2.11**	-1.21	51.91%
	Value weighted	200	0.402	3.84***	-2.52**	50.50%	69	0.275	2**	-1.43	47.83%	131	0.522	3.27***	-2.45**	51.91%
Panel C: The returns of underwriters, both high reputation and low reputation of 36 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%	N	CAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.320	1.85*	-0.40	46.34%	25	0.681	1.44	-0.28	36.00%	57	0.125	1.12	-0.58	50.88%
	Value weighted	82	0.680	3.57***	-1.91*	46.34%	25	0.693	2.44**	-1.01	36.00%	57	0.472	2.59***	-1.27	50.88%
LOWREP	Equal weighted	200	0.528	2.93***	-0.33	39.50%	69	0.527	1.19	-0.34	39.13%	131	0.082	3.27***	-0.53	39.69%
	Value weighted	200	0.561	4.75***	-2.12**	39.50%	69	0.351	2.14**	-0.92	39.13%	131	0.266	4.35***	-2.56**	39.69%

Note. The table illustrates the equally and value-weighted CARs over 36 months post-listing, excluding the initial return. The conventional t-statistics (t-stat). The non-parametric Wilcoxon Signed Rank test (s-stat). Statistical significance levels are represented by ***, **, and *, denoting significance at the 1%, 5%, and 10% levels, respectively. This addresses the long-term performance of initial public offerings (IPOs) in Thailand, especially those associated with venture capital (VC) and private equity (PE), alongside the Underwriter Reputation. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

Table 7: Analyzes BHARs returns of Thai IPOs by underwriters and backed & non-backed VC/PE over 12, 24, and 36 months.

Panel A: The returns of underwriters, both high reputation and low reputation of 12 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.191	2.21**	-1.59	56.10%	25	0.343	2.01**	-1.33	44.00%	57	0.125	1.25	-1.47	61.40%
	Value weighted	82	0.486	2.63***	-1.97**	56.10%	25	0.507	1.83*	-1.95*	44.00%	57	0.472	1.84*	-1.62	61.40%
LOWREP	Equal weighted	200	0.089	1.9*	-1.98**	61.00%	69	0.101	1.52	-1.28	50.72%	131	0.082	1.32	-0.97	66.41%
	Value weighted	200	0.281	3.07***	-2.05**	61.00%	69	0.294	1.95*	-1.58	50.72%	131	0.266	1.01	-1.52	65.65%
Panel B: The returns of underwriters, both high reputation and low reputation of 24 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.228	2.13**	-1.63	56.10%	25	0.428	2.21**	-1.71*	48.00%	57	0.140	1.10	-1.73*	59.65%
	Value weighted	82	0.690	3.1***	-1.67*	56.10%	25	0.770	2.26**	-1.98**	48.00%	57	0.622	2.1**	-1.04	59.65%
LOWREP	Equal weighted	200	0.058	1.09	-2.12**	64.00%	69	0.022	0.26	-1.47	65.22%	131	0.077	1.12	-1.96*	63.36%
	Value weighted	200	0.407	2.91***	-1.91*	64.00%	69	0.340	1.59	-1.02	65.22%	131	0.469	2.49**	-2.1**	63.36%
Panel C: The returns of underwriters, both high reputation and low reputation of 36 months																
		ALL FIRM					BACKED VC&PE					Non BACKED PE&VC				
		N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%	N	BHAR	t-stat	s-stat	Obs <0.0%
HIGHREP	Equal weighted	82	0.139	1.21	-0.75	60.98%	25	0.464	1.93*	-0.96	44.00%	57	-0.003	-0.02	-0.69	68.42%
	Value weighted	82	0.791	2.69***	-1.20	60.98%	25	0.902	2.16**	-1.25	44.00%	57	0.696	1.66*	-0.50	68.42%
LOWREP	Equal weighted	200	0.189	2.39**	-1.60	60.00%	69	0.024	0.25	-0.67	63.77%	131	0.276	2.52**	-1.75*	58.02%
	Value weighted	200	0.607	3.25***	-1.99**	60.00%	69	0.412	1.57	-1.04	63.77%	131	0.777	2.87***	-2.63***	58.02%

Note. The table presents equally and value-weighted BARs over 36 months post-listing, excluding initial return, with conventional t-statistics (t-stat) and non-parametric Wilcoxon Signed Rank test (s-stat). Significance levels are indicated by ***, **, and *, representing significance at the 1%, 5%, and 10% levels respectively. This analyzes the long-term performance of Thai IPOs, particularly those linked with venture capital (VC) and private equity (PE), along with Underwriter Reputation. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

Our objective is to look into the underperformance of initial public offerings (IPOs) over the long run that underwriters are blamed for (Agathee et al., 2014). From the Thailand SEC website, we were able to obtain a list of issuers that were involved in transactions. We created a ranking system based on particular metrics from 2009 to 2020, even though our data might not include all worldwide issuers. We started by looking at the overall deal size in terms of offer size, which we obtained from the SEC website, in order to assess underwriter reputation. Prior research indicates that reputable or well-known underwriters tend to handle larger offerings, which translates into higher scores in our ranking system (Carter and Manaster, 1990). We also created a similar scoring system based on the number of deals that the underwriters had completed. We postulated that underwriters who have a higher volume of deals along with larger deals are seen as more reliable. Using a percentage rank formula, we computed scores for each underwriter using equal steps for each measure, resulting in a total score of 10. Then, we used this score to construct a dummy variable that would identify the "Top 3 underwriters," with the goal of determining whether or not being a top underwriter is associated with lower long-term underperformance. To investigate whether being a top underwriter is associated with a lower rate of long-term underperformance, we utilized this score to create a dummy variable that indicated the "Top 3 underwriters".

We find consistent results using cumulative abnormal return (CAR) and buy-and-hold abnormal returns (BHAR) over 12-, 24-, and 36-month periods to test the hypothesis of Backed PE & VC with highly reputable underwriters in Tables 6 and 7. The best performance is shown across all periods by backed PE & VC with reputable underwriters; s-statistics are significant at the 10% to 5% level. BHAR value-weighted VC&PE with a good reputation has the highest return, at 90.2%, while BHAR equally weighted VC&PE with a poor reputation has the lowest performance, at 2.2%. But there's a big difference between the results from BHAR and CAR. Results regarding backed and unbacked VC&PE issues in the hot issue market indicate that BHAR has higher significant s-statistics than CAR, with the former showing lower significance. However, overall results are consistent with (Doukas and Gonenc, 2000) and support the hypothesis that Backed PE & VC with well-regarded underwriters will show less long-term underperformance.

4.3) Regression of Long Run Performance

As explained in the methodology, Tables 8 and 9 present the performance results of our model. The 12-, 24-, and 36-month CAR models' adjusted R-squared values are negative, indicating that their predictive power is constrained. BHAR, on the other hand, indicates some improvement with values of -0.0202, 0.0094, and 0.0034. The 12-month BHAR, in particular, provides interesting information: the VC & PE dummy has a 0.0558 beta, indicating that companies backed by PE may have a 5.58% higher BHAR (not statistically significant, in line with (Achima Chalarat, 2018).

Similarly, underwriting reputation (REP) exhibits a beta of 0.1089, suggesting a possible improvement of 10.89% (also not statistically significant). Independent variable betas frequently go negative over extended periods of time, potentially signaling market corrections. According to Kaplan et al. (2005) and Bergström et al. (2006), hot-issue market listings typically have poor long-term performance. Unlike variables like age and assets, 12-month BHAR for market capitalization (MCAP) and offer size (OFFERSIZE) in our uncertainty model is significant at the 10% level, suggesting some explanatory power. In contrast with (Poulsen & Breuner Nielsen, 2017), who discovered significant explanatory power for long-term performance, the explanatory power of uncertainty variables decreases with time.

Table 8: Regression for 12-, 24- and 36-months CAR

SUMMARY OUTPUT			
	CAR		
Variables	12 Months	24 Months	36 Months
Intercept	-0.4311	-0.0398	0.8507
	(0.2074)	(0.9668)	(0.4388)
REP	0.0188	0.0415	-0.1615
	(0.8418)	(0.8752)	(0.5942)
PE(VC)	0.0499	0.3118	0.2282
	(0.593)	(0.2343)	(0.4478)
Hot	-0.1327	0.0624	0.1783
	(0.1588)	(0.8129)	(0.5553)
OFFERSIZE	-0.6932	-0.7262	-0.6606
	(0.1267)	(0.5673)	(0.6503)
AGE	0.0000	0.0008	-0.0003
	(0.9954)	(0.8068)	(0.9388)
ASSET	0.0649	0.1019	0.0452
	(0.5785)	(0.7555)	(0.9043)
MCAP	0.6954	0.5655	0.3429
	(-0.131)	(0.6607)	(0.8166)
Multiple R	0.1527	0.0858	0.0975
Adjusted R Square	-0.0016	-0.0180	-0.0158
Observations	282	282	282
F-Statistic	0.9339	0.2905	0.3754

Table 9: Regression for 12, 24 and 36 months BHAR

SUMMARY OUTPUT			
	BHAR		
Variables	12 Months	24 Months	36 Months
Intercept	-0.6156 *	-0.6407	0.1256
	(0.0681)	(0.1058)	(0.8139)
REP	0.1089	0.1703	-0.0498
	(0.2412)	(0.1192)	(0.7353)
PE(VC)	0.0558	0.0178	-0.0343
	(0.5445)	(0.8689)	(0.814)
Hot	-0.1177	-0.1046	-0.0350
	(0.2042)	(0.3367)	(0.8117)
OFFERSIZE	-0.8551 *	-0.7196	-0.3287
	(0.0561)	(0.1706)	(0.6422)
AGE	-0.0002	-0.0005	-0.0017
	(0.8789)	(0.6994)	(0.3754)
ASSET	0.0563	-0.0034	0.0479
	(0.6248)	(0.9799)	(0.793)
MCAP	0.8814 *	0.8276	0.2661
	(0.0525)	(0.1207)	(0.711)
Multiple R	0.1845	0.1681	0.0723
Adjusted R Square	0.0094	0.0034	-0.0202
Observations	282	282	282
F-Statistic	1.3798	1.1385	0.2055

Note. The table reports output from a multivariate regression of 12-, 24-, and 36-months CAR and BHAR with 7 predictors. REP is a dummy variable, taking the value 1 if the underwriter is among the top 3 in Thailand and 0 otherwise. PE and VC is a dummy variable, taking the value 1 if the company is Venture Capital and Private Equity backed, or 0 otherwise. Hot Market is a dummy variable, taking the value 1 for IPOs above the median in the 3-month moving average distribution and 0 for those below the median. Offer size is the IPO firm's offer size in million baht, using logarithms. Age is the number of years before the IPO. Assets is the total assets of the company in the issue year in million baht, using logarithms, which is relevant to the size of the firm. Market Capitalization at Offer is the market cap at offer quoted in million baht, using logarithms. Statistical significance levels are represented by ***, **, and *, denoting significance at the 1%, 5%, and 10% levels, respectively, with the number representing the coefficient of the variable and the value in brackets representing the p-value. Adapted from "Under-pricing and long-run performance of Initial Public Offerings in developing markets the case of Thailand" by Komenkul, K., 2015.

5) Conclusion

5.1) Summary of results

The current investigation utilized data from 282 Thai stocks spanning the years 2009 to 2020 to reevaluate the long-term performance of initial public offerings (IPOs) in Thailand. This study differs from earlier research (e.g., Allen et al., 1999; Chorruk and Worthington, 2010; Komenkul, 2015) in four significant ways. First, it employs updated data, including a COVID-19 dataset, before benchmarking against the SET and MAI segments. Second, unlike previous studies that relied solely on equally-weighted returns, this research constructs both equally-weighted and value-weighted IPO portfolios for performance measurement. Third, it compares the performance of firms in Hot and Cold Markets, with findings indicating that Hot Markets perform worse, consistent with Kooli and Suret (2004). Additionally, it categorizes long-term performance based on Hot and Cold Markets, as well as issues involving Backed VC & PE and Non-Backed VC & PE. Finally, the study compares the long-term performance of various underwriters, as well as backed versus non-backed venture capital and private equity issues.

According to the study, which is in line with earlier findings, IPOs in Thailand underperformed over the long term when evaluated using equally-weighted event-time CARs and BHARs. Furthermore, IPOs by larger companies had worse long-term returns than those by smaller companies. Nonetheless, over a three-year holding period, value-weighted returns showed outperformance against the market. Moreover, the original hypothesis was rejected because IPOs issued in hot markets and those backed by VC and PE underperformed in comparison to their peers. In value-weighted portfolios, however, well-known companies and those with backed venture capital and private equity outperformed others. However, in terms of the uncertainty variables in long-term performance, the regression analysis did not find statistically significant results for VC & PE, which is consistent with (Achima Chalarat, 2018) but different from (Poulsen & Breuner Nielsen, 2017).

5.2) Limitations of the Study

In this study, data from SETSMART and SEC Thailand were used to examine the long-term returns of securities from 2009 to 2020. Samples were taken from the Market for Alternative Investment and the Thailand Stock Exchange. After removing securities that were delisted within a three-year period in order to prevent survival bias, the initial sample of 286 companies was subsequently reduced to 282. The size of the securities in relation to market capitalization was not broken out in the report. Furthermore, for three years, the value-weighted portfolio ignored any possible share issuances by using the same share number. The SEC's 69-1 report was the primary source of the data on VC&PE. The lack of clear identification in the shareholder section raised concerns about selection or sampling bias. Finally, to determine market-adjusted returns for abnormal securities, the report used the BHAR and CAR techniques.

5.3) Policy Recommendations

The long-term returns of securities that are made available to the public on the Stock Exchange of Thailand and the Market for Alternative Investment (MAI) are examined in this study. It highlights better long-term returns in both categories by contrasting these returns with market performance. Investors navigating securities investments must take note of these findings. Furthermore, the study suggests utilizing techniques such as the Fama-French three-factor model or CAPM to improve estimates of expected returns calculations. Deeper insights may also be obtained by using alternative abnormal return models, such as Calendar-time abnormal returns, which are based on specific benchmarks or models, such as CAPM. For the portfolio performance analysis, Wealth Relative (WR) can be utilized alongside market indices or benchmarks. Additionally, categorizing each portfolio into distinct sectors allows investors to gain valuable insights into sector performance. This approach enables a deeper analysis, highlighting specific areas of strength and opportunity within the portfolio and ultimately guiding more informed investment decisions.

Regarding suggestions for policy, the results of this analysis are crucial in helping to make wise financial choices and develop successful investment plans. Through a thorough analysis of IPOs' long-term performance, this report offers insightful information about possible risks and rewards. Investors need to know this information in order to assess market reactions and the effects of particular policies. Moreover, the noted IPOs' long-term underperformance emphasizes how critical it is to improve market efficiency. By encouraging fair market practices, competition, and transparency, policymakers can have a significant impact on improving market efficiency. Policymakers can play a major role in determining the long-term performance of initial public offerings (IPOs) by establishing a regulatory framework that places a high priority on accountability, transparency, and fair disclosure.

Additionally, the discovery of underperformance trends among initial public offerings (IPOs) in wealthy markets highlights the importance of careful policy-making. To prevent overheating, policymakers should remain vigilant for market bubbles and take proactive measures to mitigate them. By implementing strategies to reduce the risks associated with IPOs issued during times of market enthusiasm, policymakers can help ensure long-term market stability and maintain investor confidence.

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The Relationship between ESG and Financial Performance of The Companies Listed in SET50

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Abstract

This study aims to examine the impact and relationship between ESG scores (ESG) and ESG criteria separately; Environmental scores (ENV), Social scores (SOC), and Governance scores (GOV) over financial performances (FP) by using dataset of 50 firms listed in the Stock Exchange of Thailand (SET50). To measure financial performance, we employ three different dependent variables of Tobin's Q (TBQ), Return on Equity (ROE), and Return on Asset (ROA). Develop hypotheses and test them by applying regression analysis and using correlation matrix, descriptive statistics with panel data drawn from Bloomberg database and Settrade to analyze data of companies listed in SET50 which spans the years 2020 to 2023. Our findings suggest that ESG combined score is positively and significantly associated with ROA. Individual Environmental and Social scores have a positive and significant relationship while Governance score does not have a significant relationship with ROA. On the other hand, only social scores have a positive and significant relationship with ROE. Results of Tobin's Q suggest that Environmental scores have a positive and significant relationship, but social scores have a negative and significant relationship with Tobin's Q. These findings imply that investing in strong ESG performance yields financial returns for the firm, enhancing both its value and profitability.

Keywords: ESG scores (ESG), ESG criteria, Environmental scores (ENV), Social scores (SOC), Governance scores (GOV), Financial performances (FP), Tobin's Q (TBQ), Return on equity (ROE), Return on asset (ROA)

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Investor Behavior in the Stock Exchange of Thailand: A Behavioral Finance Investigation

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Abstract

Recently, behavioral finance theory has gained increasing attention by providing explanations for empirical findings that traditional financial theories cannot account for. The growing acceptance of behavioral approaches in finance reflects a shift in conceptual understanding. This study delves into the complex world of investor behavior in the Stock Exchange of Thailand from a comprehensive behavioral finance perspective. It examines the impact of psychological factors on risk-taking behavior in investment decisions. Specifically, this study explores the potential effects of psychological factors such as herding, heuristics, prospect, market, self-attribution bias, and familiarity bias on the decision-making process in investments. Data was collected through questionnaires from a sample of 400 individuals. The study aims to identify recurring patterns of anomalies that contribute to the fluctuations in the Thai stock market. The findings reveal that herding factor, market factor, prospect factor, and familiarity bias significantly impact risk-taking behavior in investment decisions among Thai stock market investors. It is anticipated that herding factor will lead to increased market risk and overall volatility in the Thai stock market. Meanwhile, prospect factor and market factor tend to result in higher risk-taking among investors, and familiarity bias leads to a lack of diversification in investment portfolios. This study aims to provide valuable insights for both market participants and regulatory bodies.

Keywords: Behavioral Finance, Risk-Taking Behavior, Stock Exchange of Thailand

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