Optimizing Thai equity portfolios with CANSLIM and APT strategies

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Bachelor of Engineering in
Financial Engineering
School of Engineering
King Mongkut’s Institute of Technology Ladkrabang
Academic Year 2023

เอกสารนี้เป็นเอกสารที่สงวนไว้สำหรับการใช้งานเพื่อการศึกษาเท่านั้น ไม่อนุญาตให้นำไปใช้ประโยชน์ด้านการค้า
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Acknowledgement

We express our deepest appreciation and gratitude to Assoc. Prof. Nada Chunsom, Dr. Pimprapai Thainiam, and especially Mr. Surashate Sriwattanakulwong, Mr. Thanasarn Porthaveepong, and Mr. Wongsakorn Hemphan, along with the entire KWIAM team, for their invaluable guidance and support throughout our senior thesis project. We extend our heartfelt gratitude to Assoc. Prof. Nada Chunsom for her technical expertise in the financial field and consistent support throughout our project. Her assistance in navigating technical aspects, offering insightful advice, and providing constructive criticism significantly contributed to the project's success. We are truly grateful for her dedication and commitment.

We are particularly thankful to Dr. Pimprapai Thainiam for her coordination and facilitation of research and development, which greatly contributed to the successful completion of our project.

We also acknowledge the significant contributions of three individuals to our work. Firstly, Mr. Surashate Sriwattanakulwong provided valuable suggestions on methodology, research processes, and data organization, enriching our project development. Secondly, we appreciate Mr. Thanasarn Porthaveepong for his assistance in data structure, portfolio algorithm, and troubleshooting support. Lastly, Mr. Wongsakorn Hemphan's contributions to model construction and framework greatly influenced our portfolio methodology.

For their invaluable guidance and expertise in model development, sincere gratitude is extended to Dr. Jing Tang and Assoc. Prof. Yuthana Sethapramote, Ph.D. Their generous contributions have greatly enriched the completeness of this project.

We sincerely thank our advisors and friends for their time, effort, and dedication to our project. Working alongside such extraordinary advisors has been an honor, and we are immensely grateful for their assistance and guidance.

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Abstract

This proposal outlines a comprehensive approach to optimizing Thai equity portfolios by integrating the CANSLIM investment strategy with the Arbitrage Pricing Theory (APT) framework. CANSLIM, a well-established investment methodology pioneered by William O'Neil, emphasizes fundamental factors to identify high-potential stocks. On the other hand, APT offers a multifactor model to assess security returns based on various market risk factors.

The revised methodology integrates the complementary strengths of multiple strategies to construct diversified portfolios that optimize growth potential while mitigating risk. Through comprehensive quantitative analysis of historical market and financial data for Thai equities, the study constructs models to analyze individual stock returns. Subsequently, the research examines the dynamic interplay between these models and their implications for portfolio performance, ensuring a robust foundation for informed investment decisions.

Key objectives include developing a robust investment framework that combines the principles of CANSLIM and APT, optimizing portfolio allocation strategies, and evaluating the performance of the constructed portfolios against benchmark indices. The study will also investigate the potential for outperformance compared to passive investment approaches.

By employing advanced quantitative methods and leveraging insights from both CANSLIM and APT, this research aims to provide valuable insights into portfolio optimization strategies tailored to the Thai equity market. The findings are expected to contribute to the body of knowledge in investment management and offer practical guidance for investors seeking to enhance their portfolio performance in the Thai equity market landscape.

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Chapter 1
Introduction

1.1 Motivation

In the dynamic landscape of modern finance, the construction and management of equity portfolios represent a multifaceted and intricate challenge. Traditional investment approaches, often employed in this endeavor, frequently struggle to achieve the optimal balance of risk and return. Recognizing these intricacies and driven by a steadfast commitment to advancing the art of portfolio management, we embark on a transformative journey. Our project is grounded in a resolute aim to revolutionize Thai equity portfolio management, harnessing the power of a multifactor investing model. This endeavor seeks to streamline and automate the portfolio construction process, attain risk-return equilibrium, benchmark against the SET Total Return Index, empirically validate the significance of each factor, and uphold the pinnacle of research excellence.We seek to substantiate the model's historical performance and real-time adaptability, all with an unwavering determination to consistently deliver Thai equity portfolios that yield high risk-adjusted returns, thus setting new benchmarks for excellence within the ever-evolving Thai equity market.

Drawing inspiration from the CANSLIM investment strategy, which has demonstrated its effectiveness in the Thai stock market, yielding high returns of up to 252.2% from 2009 to 2015, particularly in bull markets, our study finds its roots in the exploration

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of multifactor models. Building upon recent research such as "Profitability, Investment and Asset Pricing: Reconciling the Valuation and the q-Theory Approaches in the Thai Stock Market" by Kanis (2020), our investigation delves into the nuanced performance of the valuation-based Fama-French and capital-budgeting-based q-factor models in the Thai stock market. Kanis's study highlights the ambiguous effects of each model's two factors regarding EG and UMD, suggesting that q-factor models may outperform their Fama-French counterparts. This discovery sparked our interest in the q-factor model, which encompasses market risk (MKT), Size (ME), Profitability (ROE), and Investment (I/A), along with various conceptual and industry variables. By integrating CANSLIM into our multifactor approach, we aim to optimize portfolio construction, enhance returns, and navigate the complexities of the Thai equity market with empirical precision and data-driven decisions.

1.2 Objectives

1. To create an innovative multi factor investing model to optimize the construction of Thai equity portfolios, enhancing risk-adjusted returns and portfolio efficiency.
2. To conduct empirical testing to confirm the significance of each factor integrated into the multifactor model, contributing to the body of financial knowledge.
3. To uphold the highest standards in research methodology, aiming to consistently deliver Thai equity portfolios that generate high risk-adjusted returns.
4. To gauge practical relevance and benefits by Comparing the performance of the constructed portfolios against the SET Total Return Index (SET TRI).

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1.3 Scope of Work

The scope of this project can be listed in two type as follows:

1.3.1 Research Framework

1. To establish a Thai equity portfolio, employing a multifactor screening approach for stock selection, portfolio construction, and risk management is the primary goal of this project.
2. To optimize portfolio construction in Thailand by selecting the most suitable methodology for the best stocks is the expected result of this project.
3. To adhere to the condition, the Thai Equity Portfolio will consist of 15-30 stocks from SET100.

1.3.2 Conceptual Framework

1. Researching: Conduct literature review relevant to the project objectives.
2. Data Collection: Gather historical data of overall stocks from the stock exchange in Thailand.
3. Stock Screening: Select stocks for the portfolio based on fundamental and technical analysis.
4. Multifactor Model Development: Develop a model for stock selection and estimate the expected return of individual stocks.
5. Portfolio Construction: Construct optimal portfolios based on criteria from the research framework and construction criteria.
6. Performance Measurement: Evaluate and visualize portfolio performance within the constructed framework.
7. Rebalance Portfolio: Implement a risk management and rebalancing management framework to ensure portfolio stability and performance optimization.

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1.4 Thesis Structure

This thesis consists of five chapters which are arranged as follows:

- Chapter 1 Introduction - refers to the motivation, objectives, scope of work, and thesis structure of this thesis.
- Chapter 2 Literature Review – proposes the Literature survey that are relevant to this project, and comparison.
- Chapter 3 Background Knowledge - explains the knowledge and theory necessary for the reader to understand the thesis.
- Chapter 4 Research Methodology - This chapter elucidates the methodology employed to conduct the research and formulate the requisite multifactor model and portfolio.
- Chapter 5 Results and Discussion - presents the results obtained from the research conducted and discusses them in detail, analyzing their implications and limitations.
- Chapter 6 Conclusion and Recommendations - summarizes the research work done, restates the conclusions derived from the study, and suggests possible recommendations for future work in this field.

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Chapter 2
Literature Review

This chapter offers an in-depth examination of multifactor models for investment and portfolio construction, encompassing CANSLIM, APT, related factors, portfolio allocation strategies, and performance measurement techniques [Appendix 1.1A and 1.2A].

2.1 CANSLIM

Thanakorn Pisudsin (2016) research in the study on the model of stock price that the CANSLIM system screening on the stock exchange of Thailand consists of current quarterly earning, annual earning, new product, supply & demand, leader or laggard, institutional sponsorship and market direction to selection stocks into portfolio and construct portfolio and separator in 3 cases, First screen stock by CANSLIM each quarterly, analyze return from portfolio construction during 9 years and analyze factor that has an impact on goal price, has volume factor PE factor and on-balance factor to calculate the probabilities of the stock success to goal. In summary, research concludes that the CANSLIM investment strategy can be effectively applied in the Thai stock market, yielding high returns of up to 252.2% from 2009 to 2015. The study also suggests a correlation between trading volume and future securities returns, reinforcing the success potential of breakout price patterns during price compression phases. When comparing annual returns, CANSLIM outperforms the market, achieving an average return of 84.1% compared to the market's 24.6%. The breakout price patterns Double Bottom and Cup with Handle were the most common during the study.

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2.2 CAPM and APT

Wiratson Srisap (2005) aimed to analyze and compare the Return Over Risk following the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT). This study investigated the relationship between the returns of five main asset groups in the entire industry, namely banking, securities companies, energy, communication, and real estate development. The economic factors studied included inflation rate, USD to THB exchange rate, interbank lending rate, interbank borrowing rate, private sector investment, oil prices, and industrial production index. Utilizing monthly data from January 2002 to December 2008, employed the 12-month fixed deposit rate of commercial banks as the risk-free asset. The study tested the stationarity of data using the Augmented Dickey-Fuller Test (ADF) and then estimated risk using Ordinary Least Squares (OLS) regression analysis.

The study revealed that the Capital Asset Pricing Model (CAPM) can explain the returns of all three main asset groups: banking, securities companies, and energy. Conversely, the Arbitrage Pricing Theory (APT) can explain the returns of all main asset groups except for the energy sector. Statistically significant economic factors that explain the variations in returns for the CAPM include changes in the interbank lending rate, which can explain the changes in returns for the banking and securities sectors. Additionally, exchange rate changes (THB to USD) can explain the changes in returns for the banking and securities companies' groups. The comparative analysis between the CAPM and the APT indicates that the CAPM has higher decision-making efficiency in all main asset groups, suggesting it can better explain the relationship between returns and risk for both industry groups. However, the APT, while less efficient in decision-making, can explain the relationship between returns and risk across multiple asset groups, surpassing the CAPM. Therefore, in analyzing the relationship between returns and risk, it is advisable to choose the APT over the CAPM due to its incorporation of multiple economic factors, making it a more comprehensive tool for investors seeking optimal returns aligned with the economic conditions prevailing at that time.

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2.3 Fama-French 6 factor and q-theory

Kanis SaengChote (2020) research profitability, investment and asset pricing by reconciling the valuation and the q-theory approaches in the Thai stock market. Comparing Fama-French 6 factor model consists of market risk(MKT), size(SMB), value(HML), and profitability(CMA) and momentum(UMD) and Q-factor model 5 factor consists of market risk(MKT), size(ME), investment(I/A), profitability(ROE) and expected growth(EG). Construct mimic portfolios, Fama-French (2018) sixes factor model by double-sorting (2x3) portfolio and Q-5 actors model with triple-sorting (2x3x3) portfolios then got 18 portfolio and use GRS Statistic test and intercept test in test assets. Using alpha asset test in each factor by factor spanning regression of individual factors. The result can conclude, the performance of the valuation-based Fama-French and the capital-budgeting based q-factor models in Thailand and found both models perform well, but on different aspects which the strengths of the two into a better-fitting model that incorporates market risk, size, value, profitability and investment effects. but the q-factor seems better than the Fama-French 5 factor. Our group is interested in the q-factor model and want to construct a portfolio by this asset pricing model. Besides the conventional metrics, various other factors significantly impact constructing an investment portfolio. Our research aims to identify and evaluate more additional factors that influence stock prices.

2.4 Factor related to commercial banking sector

Athiphat Rojanawutthitikhun (2011) conducted an analysis of securities prices in the commercial banking sector on the Stock Exchange of Thailand from the year 2005 to 2010 using four economic factors as independent variables: inflation rate, real deposit interest rate, average dividend yield, and Real GDP. The analysis was carried out in two formats: 1) Descriptive Analysis: This involved transforming the data into percentage proportions to explain the factors that impact the prices of securities within the commercial banking sector on the Stock Exchange of Thailand. 2) Quantitative Analysis: The data was subjected to a Multiple Linear Regression analysis using the

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Ordinary Least Square Method to determine the coefficients of the independent variables.

The study revealed a significant relationship between Real GDP and the prices of securities in Thailand's commercial banking sector, with a 95% confidence level. Real GDP serves as a comprehensive indicator of the national economy, influencing investor confidence in these securities, and is impacted by a range of domestic and international economic factors. Notably, the economic slowdown in the United States, Thailand's major trading partner and the world's largest economy, had a substantial impact on Thailand's economy due to their economic interdependence, leading to repercussions on Thailand's economic performance.

Rattanaporn Saelee and Sumamarn Pankham (2021) conducted a study on the factors influencing the stock prices of commercial banks in the Stock Exchange of Thailand and compared these factors with those affecting stock prices in this sector. The factors under examination included the Dow Jones Industrial Average (DJIA), Exchange rate (USD/THB), SET Index, Consumer Price Index (CPI), and inflation rate (INF). The research followed a quantitative approach, utilizing secondary data in the form of monthly time series data from January 2011 to December 2020, covering a total of 120 months. Data analysis involved determining the coefficients of each independent variable, followed by regression analysis using the Stepwise Regression and Enter Regression methods for variable selection.

The study found that factors affecting the stock prices in the commercial banking sector in the Stock Exchange of Thailand include the Dow Jones Industrial Average (DJIA). The DJIA is considered a factor that influences stock prices because it serves as an indicator of market conditions and the economy in the United States, a leading global market. Therefore, individual investors use the DJIA for analysis and to compare market conditions before buying or selling securities. This analysis has an impact on the trading activity of retail investors in the same direction. This is in line with the research conducted by Thanyarat Saengsuriyaroj, Pramin Kositkulphon, and Sombat Kachayuth in 2020. The USD/THB exchange rate is a factor that influences stock prices because changes in the exchange rate of the Thai Baht to the US Dollar

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have an impact on foreign investors' holdings in Thailand. When the Baht strengthens, foreign investors in the country tend to sell securities due to concerns about the returns from the exchange rate, leading to a decrease in stock prices. This finding is consistent with the research conducted by Chamnongjit Pumakhom in 2010. The SET Index, which is the stock price index of the Stock Exchange of Thailand, is a significant factor affecting stock prices in the same direction, as it reflects the overall movement of stock prices in the market. For example, if the SET Index rises, it signals an improved Thai economy, which boosts consumer confidence and buying power. This, in turn, leads to business growth and increased stock prices, encouraging investors to invest. This finding aligns with the research by Supawat Thanasirihiransuk in 2011. Additionally, the Consumer Price Index (CPI) is a factor that affects the stock prices of commercial banks in the opposite direction because it measures changes in the prices of goods and services over time and serves as an indicator of inflation. When the CPI increases, purchasing power decreases, and consumers need to reserve more money for consumption, reducing the available funds for investment in securities and causing stock prices to decline. This corresponds to the findings of Suwapit Banluerit in 2011 and Suphawat Thanasirihiransuk in 2011.

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2.5 Factor related to various industry groups

Supitcha Tirapat (2012) examined the economic factors influencing the movement of stock price indices in five industry groups on the Stock Exchange of Thailand, comprising Energy and Utilities (ENERG), Banking (BANK), Information and Communication Technology (ICT), Commerce (COMM), and Food and Beverage (FOOD). This analysis involved seven economic variables: the one-year borrowing interest rate (INT), foreign investors' securities purchase volume (FDI), general inflation rate (INF), Thai Baht to US Dollar exchange rate (EXC), crude oil price (OIL), gold price (GOLD), and the Business Sentiment Index (BSI). The study covered monthly data from January 2007 to December 2011, totaling 60 months. The analysis employed a multiple regression model and estimated the coefficients of independent variables using the Ordinary Least Square method.

The study found that economic factors influence the movement of stock price indices in different industry groups, with varying effects. The economic factors that had an impact on the stock price indices during the study period included the foreign investors' securities purchase volume, gold price, Thai Baht to US Dollar exchange rate, Business Sentiment Index, crude oil price, and the general inflation rate. Interestingly, the one-year borrowing interest rate did not significantly affect the stock price indices in any industry group.

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2.6 Portfolio allocation strategies

Theron, Ludan (2018) research about the effectiveness of four different strategies for allocating portfolios is assessed based on their absolute returns across various economic conditions spanning a decade. A comparison is made between the Most Diversified (MD) portfolio and three alternatives: a Minimum Variance portfolio, an Equally-Weighted portfolio, and a Tangent (or Maximum Sharpe ratio) portfolio. The objective is to evaluate portfolio performance using cumulative returns, the Sharpe ratio, and daily volatilities. These allocation methods are influenced by multiple factors, leading to varied performance among the portfolios. The Tangent (TG) portfolio consistently outperformed the others in terms of cumulative returns throughout most of the period, with the unconstrained TG portfolio showing particularly high returns exceeding 2,500%. Conversely, the Minimum Variance (MV) portfolio exhibited the lowest cumulative returns and the lowest daily volatility levels. The Most Diversified (MD) portfolio's performance was subpar due to ineffective diversification of assets, resulting in a lack of diversification benefits.

2.7 Performance Measurement

Risk-adjusted performance ratios assist investors in comparing the risk volatility associated with asset returns. While widely used for predicting fund performance, investors must also consider external factors like political and economic issues. This study focuses on identifying suitable ratios for evaluating Thai mutual funds across various sectors. It analyzes 279 funds from January 2013 to December 2018, validating results over two and five-year periods. Most ratios prove effective, except the Sortino ratio, which underperforms in the gold sector. Wipha Thomyamongkul (2021) luach the study highlights the importance of considering diverse factors influencing fund performance and advises against relying solely on one metric for investment decisions.

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Chapter 3
Background Knowledge

Through a succinct examination, this chapter explores key concepts and theories in the financial field, providing essential background knowledge to contextualize the research and inform subsequent objectives and methodologies.

3.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) stands as a seminal framework in financial theory, originally formulated by William Sharpe during the 1960s. It serves as a fundamental tool in financial analysis, offering insights into the expected returns of assets in relation to their inherent risk profiles. According to CAPM, the expected return $E(R_i)$ of an asset i is contingent upon its beta coefficient (β_i), which signifies its sensitivity to market fluctuations, alongside the market risk premium ($E(R_m)$ - R_f)and the risk-free rate (R_f). This relationship is expressed mathematically as:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

The model posits that investors demand compensation for undertaking additional risk beyond that of a risk-free asset, with the market risk premium representing this incremental reward. Markedly, CAPM discerns systematic risk, the form of risk that cannot be diversified away, as inherent to the broader market. This systematic risk is encapsulated by the beta coefficient within the equation. Despite its foundational assumptions and apparent simplicity, CAPM remains a linchpin in financial analysis,

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furnishing practitioners with invaluable insights into asset pricing mechanisms and portfolio management strategies.

3.2 Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT) is a model that elucidates the correlation between anticipated security returns and the risk premium derived from various influencing factors. Ross (1976) formulated the APT as an extension of Sharpe's (1964) Capital Asset Pricing Model (CAPM). While the CAPM primarily links expected security returns to the market's singular risk premium, the APT, with enhanced efficiency, adeptly elucidates fluctuations in security returns by accounting for diverse factors influencing risk compensation.

The foundational premise of the APT rests on the notion of a Perfect Market, where the securities market operates seamlessly without obstacles in buying or selling, including factors like taxes and transaction costs. Investors have the ability to diversify their investment portfolios, anticipating comparable returns on investment. Expectations of the potential returns from investments exhibit a linear relationship with the corresponding factors that impact the returns of securities. This relationship is mathematically represented as follows:

$$E(R_i) = R_f + \beta_{i_1}\lambda_1 + \beta_{i_2}\lambda_2 + \beta_{i_3}\lambda_3 + \ldots + \beta_{i_k}\lambda_k$$

Where:

$E(R_i)$	=	Expected return in stock i
R_f	=	Risk-free rate of return
k	=	Risk premium from factor k,impacting the rate of return on the stock
i_k	=	Risk value associated with factor k

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The Law of One Price is fundamental to the Arbitrage Pricing Theory (APT). This law asserts that identical goods should not be sold at different prices; thus, two securities with identical characteristics must be traded at the same price. If, however, two securities with equivalent investment outcomes have different prices, investors would engage in buying and selling these securities until prices adjust to equilibrium. The security with a higher price would decrease due to increased selling pressure, while the security with a lower price would rise as buying interest intensifies.

3.3 Fama French model

The Fama-French Five-Factor Model represents an evolution from the original three-factor model developed by Eugene Fama and Kenneth French in the early 1990s. Initially, Fama and French proposed a model that included market risk (MKT), size (SMB), and value (HML) factors to better explain stock returns. However, over time, researchers identified certain limitations in the original three-factor model, particularly in its ability to fully capture the variation in stock returns.

In response to these limitations, Fama and French extended their model in 2015 to include two additional factors: profitability (RMW) and investment (CMA). This expansion aimed to address the observed anomalies in stock returns that were not adequately explained by the original three-factor model. By incorporating profitability and investment factors, the Fama-French Five-Factor Model provides a more comprehensive framework for understanding the drivers of stock returns and offers greater explanatory power compared to its predecessor.

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The Fama-French Five-Factor Model equation is represented as follows:

$$R_i - R_f = R_f + \beta_{MKT}(R_{MKT} - R_f) + \beta_{SMB}SMB + \beta_{HML}HML + \beta_{RMW}RMW + \beta_{CMA}CMA + \epsilon_i$$

Where:

R_i	=	Return on Stock i
R_f	=	Risk-free rate
R_{MKT}	=	Return on the market portfolio
SMB	=	Size Premium
HML	=	Value Premium
RMW	=	Profitability Premium
CMA	=	Investment Premium
β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}	=	Factor Loadings
ϵ_i	=	Idiosyncratic Risk

This enhanced model has become a cornerstone in empirical finance, offering researchers and investors valuable insights into the multifaceted nature of equity returns and guiding portfolio construction strategies to better capture market dynamics and enhance performance.

3.4 Q-Factor model

The q-factor model, introduced by Hou, Xue, and Zhang (2015), is an empirical framework for asset pricing. According to this model, the anticipated return of an asset above the risk-free rate is determined by its sensitivities to various factors, including the market factor (MKT), size factor (ME), investment factor (I/A), and return on equity factor (ROE). Empirical evidence suggests that the q-factor model demonstrates significant explanatory capability and effectively captures the diversity of average stock returns across different assets. Notably, in direct comparisons with the Fama-French (2018) 6-factor model, the q-factor model emerges as superior in explaining the cross-section of stock returns.

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3.5 CANSLIM

CANSLIM, an investment strategy pioneered by William J. O'Neil in the 1980s, represents a comprehensive approach to stock selection and portfolio management, incorporating both fundamental and technical analysis. The acronym CANSLIM stands for various criteria: Current earnings, Annual earnings, New products, Supply and demand, Leader or laggard, Institutional sponsorship, and Market indices. This strategy underscores the importance of identifying stocks with strong earnings growth, innovative products or services, robust market demand, and significant institutional support, among other factors.

One noteworthy aspect of CANSLIM is its emphasis on studying the price and volume movements of stocks, using technical analysis techniques to identify optimal entry and exit points. Additionally, CANSLIM highlights the importance of market leadership, favoring stocks that lead their respective sectors or industries in terms of price performance.

Furthermore, CANSLIM's success in navigating the stock market has been empirically validated, with studies indicating substantial returns achieved through its application. Research has shown that CANSLIM can effectively identify high-performing stocks in various market conditions, offering investors a systematic framework for achieving above-average returns.

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Chapter 4
Research Methodology

This section presents an analytical framework elucidating the conceptual basis of our group work and the methodology employed in our study [Appendix 1B]

Methodology

1) Investment Philosophy
2) Population Definition
3) Data Collection and Analysis
4) Stock Screening Criteria
5) Multifactor Model Development
6) Asset Allocation Strategy
7) Performance Measurement
8) Rebalance Portfolio

4.1 Investment Philosophy

Our investment philosophy is centered on achieving optimal capital deployment of 1 billion Baht, implementing a well-structured diversification strategy with a portfolio size of 15-30 carefully selected stocks from SET100. Our primary goal is to craft a standout portfolio, emphasizing a maximum Information Ratio that reflects our unwavering commitment to performance excellence. Additionally, our investment strategy is supported by a thorough risk management framework and a robust

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rebalancing strategy. These core principles not only guide our approach but also form the foundation of our investment philosophy.

4.2 Population Definition

The population used in this research study is a Secondary Data includes The chosen securities listed on the Stock Exchange of Thailand (SET) (From our Stock Screening Process) from the second quarter of 2015 to the second quarter of 2023, of which the exact population size is known.

Utilizing the variables under investigation, we employ a model to explore the economic factors impacting the prices of individual stocks [Appendix 2B and 3B]. This model is expressed as follows:

R_i = f(Market, ME, I/A, ROE, RGDP, INF, EX, Gold, OIL, FDI, BSI, DJIA, CPI, INT, CCI, W, AOR)

Where:

- **Dependent Variable**

  R_i = Excess return in stock i

- **Independent Variable**

  - Conceptual Variable (Q-Factors):

    Market = Excess Market Return (SET Index Return - Risk Free Return)

    ME = Firm size (Book Value)

    I/A = Investment (Investment in short Asset live)

    ROE = Profitability (Return on equity)

  - Operational (Moderator) Variable:

    RGDP = Real Gross Domestic Product

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INT	=	Minimum Lending Rate
CPI	=	Consumer Price Index
W	=	Thailand Average Monthly Wages
AOR	=	3 Months Advance Booking Rate
Gold	=	Gold Price
OIL	=	Crude Oil Price
BSI	=	Business Sentiment Index
CCI	=	Thailand Consumer Confidence Index
EX	=	Exchange Rate
FDI	=	Foreign Direct Investment
DJIA	=	Dow Jones Industrial Average

The variables used in the study, according to the theory, should be those that have the strongest relationship with the structure of each industry group. The variables chosen for the study include

- Chosen Stock price: We will utilize stock price from the pick up stock as representative variables for our analysis. These indices will be compiled from the daily securities trading reports of the stock market.

- Market factor: is constructed as the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate obtained from the Bank of Thailand and measured in the market risk. It reflects the overall performance of the Thai stock market; a rising SET Index is generally associated with higher stock prices, and vice versa.

$$Market = (Return\_Market - Return\_Risk\_Free)$$

- Size Factor (ME): The Size factor, measuring a firm's size, is a crucial determinant closely linked to its overall financial structure.

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Specifically, when considering the impact of book value — calculated as the difference between a company's assets and liabilities — on a firm's performance, the true influence of size becomes apparent. The Size factor, often assessed through metrics such as book value, wields a significant impact on stock prices. It affects key aspects, including liquidity, risk perception, and growth potential. Larger companies, typically associated with higher book values, are often perceived as stable investments, whereas smaller companies, with lower book values, are deemed to present greater growth potential albeit with added volatility.

$$Book\,Value \;=\; Total\;Assets \text{ - Total Liabilities}$$

- Investment factor (I/A) : in financial models like the Fama-French and Q-Factor models measure the performance difference between companies that invest heavily (high investment-to-assets ratio) and those that do not (low investment-to-assets ratio), with companies characterized by high investment tending to have lower expected returns in the model.
- Profitability (ROE) factor measures profitability of the firm associated with the investment “high investment firms tend to have higher levels of profitability, using return on assets. A company's profitability by assessing its ability to generate earnings from its assets, and it can significantly affect stock prices, as a higher ROA often reflects efficient asset utilization and strong financial performance, potentially leading to increased investor confidence and higher stock prices.

The factors used as proxies for economic conditions that impact in each stock are as follows:

- Real GDP (Real Gross Domestic Product: RGDP) or economic prosperity, as measured by the growth of the total output of a country's

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goods and services, has an impact on the expected returns. In other words, an increase in Real GDP is associated with higher expected returns, as the rise in Real GDP instills greater economic confidence, which, in turn, leads to increased investor confidence.

- Minimum Lending Rate (INT) reflects the minimum interest rate set by banks for lending purposes. Changes in minimum lending rate can directly influence borrowing costs, thereby impacting corporate profitability and subsequent stock prices.

- Consumer Price Index (CPI): is a measure of the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services. A rising CPI can lead to concerns about the eroding purchasing power of consumers, potentially prompting central banks to raise interest rates to combat inflation, which can negatively impact Thai stock prices as higher rates may increase borrowing costs and reduce corporate profits.

- Income (W) or Thailand Average Monthly Wages can positively impact stock prices as it can lead to increased consumer spending, higher demand for goods and services, and potentially improved corporate profitability.

- Tourism or Advance Booking Rate (AOR) is a booking made before arriving at a hotel, restaurant, or other place. The AOR is a leading indicator which can explain a positive performance in the Service Industry for a further 3 months.

- Gold Price (Gold) During economic uncertainty, investors turn to safe-haven assets like gold, causing them to sell stocks, particularly in commodity or jewelry sectors, leading to decreased demand and lower stock prices.

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- Crude Oil Price (OIL) can have a mixed impact on Thai stock prices, with energy-related stocks potentially benefiting from higher oil prices, while industries heavily reliant on oil imports may face increased production costs, which could put downward pressure on their stock prices.

- Business Sentiment Index (BSI) which reflects the economic and business conditions in the current month and expectation in the next 3 months. A rising BSI, indicating increased optimism and confidence among businesses, can positively affect Thai stock prices by fostering a more favorable investment environment, encouraging investment and potential stock market growth.

- Consumer Confidence (CCI) measures the level of consumer confidence in economic activity. It is a leading indicator as it can predict consumer spending, which plays a major role in overall economic activity. The rising consumer confidence tends to positively influence stock prices as it signals increased consumer spending and economic optimism, which can drive corporate profits and market performance.

- Exchange Rate (USD/THB: EX), with the Thai Baht strengthening against the US Dollar, often lead to increased foreign investment in Thai stocks, potentially boosting stock prices as foreign investors find Thai equities more attractive.

- Foreign Direct Investment (FDI), because the higher levels of Foreign Direct Investment into Thailand often have a positive influence on Thai stock prices, as increased FDI signals investor confidence in the Thai economy and can lead to improved economic performance and growth prospects for companies listed on the Thai stock exchange.

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- Dow Jones Industrial Average (DJIA) is a stock market index of 30 prominent companies listed on stock exchanges in the United States. A significant movement in the DJIA can influence global investor sentiment, potentially impacting Thai stock prices as international investors reevaluate their portfolios in response to changes in the U.S. market.

4.3 Data Collection and Analysis

4.3.1 Source of Data

Acquire information from theoretical studies through comprehensive research and the collection of secondary data pertinent to the research. This involves utilizing historical data spanning 10 years and gathering information from printed media, journals, and relevant research sources. Additionally, insights will be drawn from various government and private agencies, enriching the research with diverse perspectives and comprehensive data sets as follows:

- Bank Of Thailand
- ThaiBMA
- Finnomena
- Yahoo! Finance
- Stock Exchange of Thailand
- Office of the National Economic and Social Development Council
- Bloomberg
- CEIC
- Nida Library

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4.3.2 Data Preprocessing

refers to how we convert the raw data we collect in a form that is ready to be fed to the model.

Three-Stages in Data Preprocessing

- Data Cleaning
- Data Integration and Reduction
- Data Transformation

Data Cleaning

This is particularly done as part of data preprocessing to clean the data by filling in missing values, smoothing the noisy data, resolving the inconsistency, and removing outliers. Anticipated challenges in the research and corresponding management strategies can be categorized into three types:

- Missing Value: Find a second Source, Backward-Fill in the missing values (Manually or Computed Value)

Data Integration and Reduction

These steps are designed for consolidating data from various sources into a unified repository, such as a data warehouse. Moreover, the dataset size within a data warehouse may surpass the capacity of data analysis and mining algorithms. A potential remedy is to derive a condensed representation of the dataset, significantly reducing its volume while maintaining the same analytical precision and quality of results.

Data Transformation

After completing the data cleaning, Integration and Reduction process, the last step involves enhancing data quality by employing various Data Transformation strategies. Our primary focus is to convert the data into a quarterly format, utilizing three key methods: Spot Price/Value, Summation, and Averaging. Through these transformations, we aim to refine the data by adjusting values, restructuring, or reformatting, ensuring a more consolidated and standardized representation in a

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quarterly context and percentage change. This refined dataset will serve as a robust foundation for further model development, enabling more sophisticated analyses and insights into the underlying patterns and trends.

4.3.3 Data Organization

Data organization involves managing information, addressing aspects like data stationarity, heteroscedasticity, autocorrelation, and multicollinearity. Navigating these factors optimizes data structures for robust analysis, unveiling meaningful insights from coherent datasets.

Three key Aspects of Data Analysis and Modeling

- Stationary of Data
- Correlation
- Lag Term

Stationary of Data

Stationary data is crucial for time series analysis because the presence of a strong trend or seasonality in non-stationary data can obscure underlying patterns, impeding accurate model estimation and prediction.

Testing Method

The Augmented Dicky-Fuller Test (ADF Test) test is an 'augmented' version of the Dickey-Fuller test. The ADF test expands the Dickey-Fuller test equation to include a high-order regressive process in the model.

$$y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \Delta y_{t-2} .. + \phi_p \Delta y_{t-p} + e_t$$

- If Test statistic < Critical Value and p-value < 0.05 – Reject Null Hypothesis(H0), i.e., time series does not have a unit root, meaning it is stationary. It does not have a time-dependent structure.

Since the null hypothesis assumes the presence of a unit root, that is α=1, the p-value obtained should be less than the significance level (say 0.05) in order to reject the null hypothesis. Thereby inferring that the series is stationary.

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Fixing non-stationary data

Differencing is a technique employed in time series analysis to achieve stationarity by subtracting the current observation from the previous one. The concept involves taking the first difference ($Y_t - Y_{t-1}$), second difference, or higher-order differences until the data exhibits stationary behavior, meaning that its statistical properties remain constant over time.

In Python, the implementation of differencing can be easily carried out using the `diff()` function in the pandas library, which efficiently computes the differences between consecutive observations in a time series, aiding in the preparation of data for further analysis or modeling.

Correlation

Correlation is a statistical term that refers to the intensity and direction of a relationship between variables. It shows how closely one variable's movements are linked to those of another. This relationship is typically stated as a correlation coefficient, which ranges from -1 to 1. A correlation of one represents a perfect positive association, -1 indicates a perfect negative relationship, and 0 indicates no link. To avoid multicollinearity, the correlation must exclude the variable with a correlation more than 0.7 and less than -0.7 before constructing the model.

The Correlation is computed using the formula:

$$\rho(X, Y) = \frac{Cov\,(X,Y)}{\sigma X\ \sigma Y}$$

Where:

ρ	=	Pearson product-moment correlation coefficient
Cov(x,y)	=	Covariance of variables x and y
σ_X	=	Standard deviation of x
σ_Y	=s	Standard deviation of y

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Lag Term

Determining the appropriate lag term is a fundamental step in model development. The lag term, representing the number of past observations considered in the model, is essential for capturing temporal dynamics and dependencies within the data. By selecting the optimal lag, we can effectively account for any time-based patterns, seasonality, or autocorrelation present in the dataset, ensuring that the model accurately reflects the underlying relationships between variables over time. This process helps prevent issues such as overfitting or underfitting, thus enhancing the model's predictive performance and reliability. Therefore, meticulous consideration of the lag term is indispensable in the construction of robust predictive models.

To check the appropriate lag term, we undertake a thorough examination of the data's characteristics, including the timing of declarations and the expected impact, guided by theoretical insights. Firstly, we scrutinize the temporal pattern of the variables under consideration, identifying any recurring trends or seasonality. Additionally, we assess the anticipated impact of past observations on the current state, drawing upon relevant economic or domain-specific theories. This involves analyzing how changes in the independent variables affect the dependent variable over different time periods. By integrating empirical observations with theoretical frameworks, we can ascertain the lag term that best captures the temporal dynamics and dependencies within the data, ensuring the model's accuracy and reliability.

4.3.4 Data Analysis

Multiple Linear Regression Analysis

In the analysis of the relationship between stock prices and various factors, mindfulness is applied through statistical measures such as Adjusted R^2, T-test, F-test, and Durbin-Watson, each characterized by specific calculation formulas:"

Coefficient of Determination

The Coefficient of Determination, represented by Adjusted R-square, signifies the percentage of variance in the dependent variable explained by the independent

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variables. It gauges the suitability of a set of independent variables in explaining the variability in the dependent variable. Consequently, a higher R^2 indicates a better fit of the data to the equation.

The formula used to analyze the Coefficient of Determination (R^2, Adjusted R^2) is as follows:

-> $R^2 = \frac{SSR}{SST}$

Due to SSR = SST-SSE

Thus, $R^2 = 1 - \frac{SSE}{SST}$

Where:

SSR	=	Sum of Squares due to Regression
SSE	=	Sum of Squared Errors
SST	=	Total Sum of Squares

-> $Adjusted\ R^2 = 1 - (\frac{SSE/(n-K)}{SST/(n-1)})$

T-test Statistics

The statistical value in question is utilized to assess the significance of the relationship between the dependent variable and each independent variable. It serves as a critical measure to demonstrate the statistical relevance or significance of the dependent variable within the context of the regression analysis.

The T-test statistic is computed using the formula:

$$T = \frac{b_i - \beta_i}{Sb_i}$$

When:

T represent statistic of T-test

Sb represent the standard error of the coefficient

bi represent the regression coefficient of the first independent variable

Bi represents the coefficient of the regression

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F-Test Statistics

It is a statistical value used to assess the relationship between the dependent variable and each independent variable in the equation.

The F-test statistic is computed using the formula:

$$F = \frac{MSR}{MSE}$$

When:

F represent statistic F-test

MSR represent variance between groups

MSE represent variance within groups

The formula used to calculate MSR is as follows:

$$MSR = \frac{SSR}{K}$$

When:

MSE represents the variance within groups

SRR represents the variation due to the regression line

K represent the number of independent variables

The formula used to calculate MSE is as follows:

$$MSE = \frac{SSE}{N-K-1}$$

When

MSE represent the variance within groups

SSE represent Sum of Squared Errors

K represent the number of independent variables

N represent the sample size or the number of data points

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Durbin-Watson Statistics

$$d = \frac{\sum_{t=2}^{n} (e_i - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

where T is the total number of observations and e is the residual error given by:

$$e_t = \rho e_{t-1} + v_t$$

where:

ρ is the sample autocorrelation of the residuals.

The Durbin-Watson test is employed to assess the independence of residuals in regression analysis, specifically to detect the presence of autocorrelation. Autocorrelation is considered by examining the test statistic, which falls between 0 and 4. A value around 2 indicates no significant autocorrelation. Deviations from 2 may suggest the presence of autocorrelation, with values closer to 0 indicating positive autocorrelation and values close to 4 indicating negative autocorrelation. This test is essential to ensure that the assumption of independent errors, a fundamental assumption in regression analysis, is not violated.

4.3.5 Checking Model Problem

To ensure the model's accuracy and reliability, prior to model implementation, it is imperative to proactively address issues identified during the analysis phase, with specific attention to the following:

Three key Aspects of Data Analysis and Modeling

- Heteroscedasticity
- Autocorrelation
- Multicollinearity

Heteroscedasticity

Heteroscedasticity in data analysis refers to uneven changes in the variability of observations in a predicted variable across different values of an independent variable

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or over time. This can bias the standard errors of regression coefficients, impacting the reliability of statistical tests and confidence intervals in regression models.

Testing Method

To test for constant variance one undertakes an auxiliary regression analysis: this regresses the squared residuals from the original regression model onto a set of regressors that contain the original regressors along with their squares and cross-products. One then inspects the R2. The Lagrange multiplier (LM) test statistic is the product of the R2 value and sample size:

$$LM = nR^2$$

This follows a chi-squared distribution, with degrees of freedom equal to $P - 1$, where P is the number of estimated parameters (in the auxiliary regression).

The logic of the test is as follows. First, the squared residuals from the original model serve as a proxy for the variance of the error term at each observation. (The error term is assumed to have a mean of zero, and the variance of a zero-mean random variable is just the expectation of its square.) The independent variables in the auxiliary regression account for the possibility that the error variance depends on the values of the original regressors in some way (linear or quadratic). If the error term in the original model is in fact homoskedastic (has a constant variance) then the coefficients in the auxiliary regression (besides the constant) should be statistically indistinguishable from zero and the R^2 should be “small". Conversely, a “large" R^2 (scaled by the sample size so that it follows the chi-squared distribution) counts against the hypothesis of homoscedasticity.

An alternative to the White test is the Breusch–Pagan test, where the Breusch-Pagan test is designed to detect only linear forms of heteroskedasticity. Under certain conditions and a modification of one of the tests, they can be found to be algebraically equivalent.If homoscedasticity is rejected one can use heteroskedasticity-consistent standard errors.

In Python, White's Test can be implemented using the het_white function of the **statsmodels.stats.diagnostic.het_white.**

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Fixing Heteroscedasticity

One way to fix heteroscedasticity is to transform the dependent variable in some way. One common transformation is to simply take the log of the dependent variable. For example, if we are using population size (independent variable) to predict the number of flower shops in a city (dependent variable), we may instead try to use population size to predict the log of the number of flower shops in a city.

Using the log of the dependent variable, rather than the original dependent variable, often causes heteroskedasticity to go away.

Autocorrelation

Autocorrelation is the correlation of a time series with a lagged version of itself. It measures the similarity between a given time series and a lagged version of the same time series.

Positive autocorrelation occurs when a time series is positively correlated with a lagged version of itself, meaning values tend to increase or decrease together over time. Negative autocorrelation occurs when a time series is negatively correlated with a lagged version of itself, meaning values tend to move in opposite directions over time. Positive autocorrelation can cause problems in certain time series analysis methods. It is important to check for autocorrelation in a time series and account for it when selecting and fitting models.

Testing Method

The Breusch-Godfrey test is a statistical test that is used to detect autocorrelation in the residuals of a linear regression model. It helps to detect autocorrelation at different lags and it’s applicable to both linear and non-linear models, as shown in Figure 4.1.

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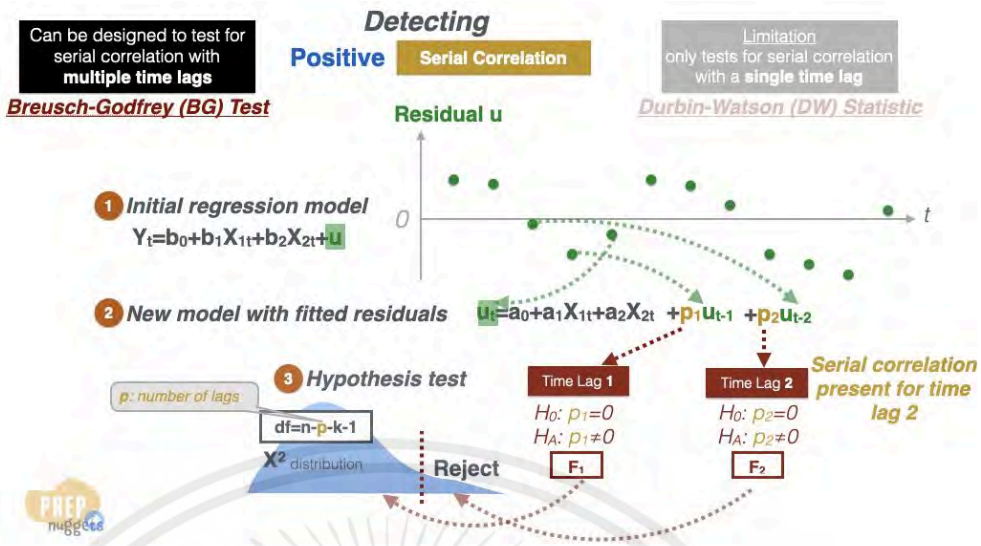

Figure 4.1: Breusch-Godfrey test (BG Test)

Source: Breusch-Godfrey test - PrepNuggets, Jan 27, 2023[7]

The test starts with an initial regression where we record down all the residuals for each time period. The residual terms are then regressed against the original set of independent variables, plus one or more additional variables representing lagged residuals. For example, we have lagged residuals for time T-1, and T-2 to test for serial correlation with 1 and 2 time lag respectively, and P1 and P2 are their coefficients. For each of these coefficients, we perform hypothesis tests on whether they are significantly different from zero, with an assumed Chi-square distribution and the degrees of freedom of p-k-1. The F-statistic is provided with most statistical software, so you just need to check it against the critical value. If we reject H-not for a particular time lag, we conclude that there is serial correlation present for that time lag.

To perform a Breusch-Godfrey test in Python, we can use the **acorr_breusch_godfrey()** function from the statsmodels library.

Fixing Autocorrelation

There are basically two methods to reduce autocorrelation, of which the first one is most important:

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- Improve model fit. Try to capture structure in the data in the model. See the vignette on model evaluation on how to evaluate the model fit: vignette("evaluation", package="itsadug").
- If no more predictors can be added, include an AR1 model. By including an AR1 model, the GAMM takes into account the structure in the residuals and reduces the confidence in the predictors accordingly.

Multicollinearity

Multicollinearity occurs when two or more independent variables in a multiple regression model are highly correlated with each other. This can create problems when interpreting the regression coefficients, as the estimated coefficients of the correlated variables can change erratically in response to small changes in the data or the model.

Testing Method

In Python, there are several ways to detect multicollinearity in a dataset, such as using the Variance Inflation Factor (VIF) or calculating the correlation matrix of the independent variables. To address multicollinearity, techniques such as regularization or feature selection can be applied to select a subset of independent variables that are not highly correlated with each other. In this article, we will focus on the most common one – VIF (Variance Inflation Factors), as shown in Figure 4.2.

VIF determines the strength of the correlation between the independent variables. It is predicted by taking a variable and regressing it against every other variable. Thus, the VIF score of an independent variable represents how well the variable is explained by other independent variables.

R^2 value is determined to find out how well an independent variable is described by the other independent variables. A high value of R^2 means that the variable is highly correlated with the other variables. This is captured by the VIF, which is denoted below:

$$VIF_i = \frac{1}{1-R_i^2}$$

Where:

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R_i^2 = Unadjusted coefficient of determination for regressing the ith independent variable on the remaining ones

So, the closer the R^2 value to 1, the higher the value of VIF and the higher the multicollinearity with the particular independent variable.

```python
# Import library for VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor

def calc_vif(X):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

    return(vif)
```

Figure 4.2 : Utilizing Variance Inflation Factor (VIF) in Python: A Comprehensive Guide

Source: Bhandari, A. (2023, November 9). Multicollinearity | Causes, effects and detection using VIF (Updated 2023). Analytics Vidhya.[8]

- VIF starts at 1 and has no upper limit
- VIF = 1, no correlation between the independent variable and the other variables
- VIF exceeding 5 or 10 indicates high multicollinearity between this independent variable and the others

Fixing Multicollinearity

We will address multicollinearity by removing one of the correlated features, reducing the interdependence between them.

4.4 Stock Screening Criteria

In this phase, we employ a meticulous selection process to identify and evaluate stocks, ultimately constructing our portfolio. The process unfolds as follows:

4.4.1 CANSLIM + PE

We initiate the stock screening process by applying the Canslim method, a systematic approach that examines a stock's fundamentals, technical indicators, and other factors

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to identify promising candidates. Our aim is to uncover stocks that exhibit the attributes outlined by Canslim, ensuring that they meet the criteria for potential inclusion.

1. C : Current quarterly earnings per share look at profit in the last quarter grew compared to the same quarter last year in which EPS should increase by at least 10%, the higher the better.

2. A : Annual earnings show strong and consistent growth and should be consistent with stable income. Look at EPS growth should exceed 10% over the last three to five years, higher better.

3. S : Scarce supply coupled with a strong appetite for a stock creates excess demand which if company stock reduces market supply and can indicate an expectation of increased demand along with insider confidence in the firm by looking at ROE should higher better and look at free float should lower better not greater than 60%.

4. L : laggard stock, use the relative strength index (RSI) should not less than 30, suggests that the stock is oversold and could be undervalued creating a buying opportunity and should not greater than 70 signifies that a stock could be overbought or overvalued and could be a chance to sell.

5. I: Pick stocks that have institutional sponsorship by a few institutions with recent above-average performance.

6. M: Market direction should choose the right time to invest when the market is up. Considering the price was higher than the exponential moving average during that period (EMA 20 & 60).

Our group places significant emphasis on stock selection criteria, which involve screening parameters such as current quarterly earnings, annual average earnings growth, new products and services, supply and demand dynamics, as well as identifying leaders and laggards in the market. Presently, the market is experiencing a bearish trend. When applying CANSLIM to screen stocks based on each factor, the outcome may not always yield viable options. Consequently, our group has opted to utilize a ranking method to identify stocks with the potential to perform well .

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In CANSLIM criteria our group decided to cut Institutional sponsorship (I) and Market direction (M) out of selection stock criteria due to it not having the score ranging measurement in the practical but it has the measurement from the adjustment of each investor.

Valuation (Fair Price)

Stock valuation is a vital step before investing, providing insights into a company's financial health and growth potential. By assessing metrics like PE ratio and earnings per share, investors can gauge if a stock is undervalued or overvalued. This process aids in identifying opportunities, managing risks, and constructing a well-balanced investment portfolio aligned with financial goals.

Comparing the Price-to-Earnings ratio (PE) of a specific stock with the industry average PE can provide insights into the stock's relative valuation. The PE ratio in each stock is calculated by dividing the stock's current market price per share by its earnings per share (EPS), Which can be written in this formula:

$$PE = \frac{Current\ Stock\ Price}{Earning\ Per\ share\ (EPS)}$$

When comparing a stock's PE to the industry average, a stock trading at a lower PE than the industry average may be considered undervalued, suggesting that investors are paying less for each unit of earnings. Conversely, a stock with a higher PE than the industry average might be considered overvalued, indicating that investors are paying a premium for the stock's earnings which is not fit to invest.

The formula of Total score:

Total Score = 1(Current) + 1(Annual) + 1(New) + 2(Supply) + L(Leader) + 0.5(PE)

In conclusion, Our group uses ranking to sort the sequence of the stock by giving the weight from CANSLIM stock screening equal to 1 and the PE valuation equal to 0.5 then calculating the total score and ranking stocks and choosing sequence 1 to 50 [Appendix 4B].

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4.4.2 Arbitrage Pricing Theory (APT)

After obtaining a list of stocks filtered through CANSLIM+PE, we will employ the APT theory for stock selection. This involves computing the 10-Year Average Return, which will be compared to the Required Return determined from the Multifactor Model [Multifactor Model Development (4.5)]. The stocks will then be categorized according to predefined criteria:

Required Return > 10-Years Average Return = Undervalued

Required Return < 10-Years Average Return = Overvalued

Subsequent to the categorization process, our investment focus will be directed towards stocks identified as 'Undervalued,' in alignment with the principles of the Arbitrage Pricing Theory (APT). According to APT, securities priced below their typical market value are expected to witness an increase in value owing to heightened buying interest, ultimately restoring market equilibrium. Embracing "Undervalued" securities offers investors a compelling opportunity for profit and contributes to market equilibrium through strategic choices.

4.5 Multifactor Model Development

Analytical Models for Variables

$$R_i = \beta_0 + \beta_1(MKT) + \beta_2(ME) + \beta_3(I/A) + \beta_4(ROE) + \beta_5(RGDP) + \beta_6(EX) + \beta_7(Gold) + \beta_8(Oil)$$
$$+ \beta_9(FDI) + \beta_{10}(BSI) + \beta_{11}(DJIA) + \beta_{12}(CPI) + \beta_{13}(INT) + \beta_{14}(CCI) + \beta_{15}(I) + \beta_{16}(AOR) + e$$

when:

R_i	=	Excess return in stock i (Total Return Index) (%)
MKT	=	Market risk premium (Return market – Risk free) (%)
ME	=	Firm size (Book Value)
I/A	=	Investment (Investment in short Asset live)
ROE	=	Profitability (Return on equity)
RGDP	=	Real GDP (Baht)
EX	=	Exchange Rate (USD/THB)

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Gold = Gold Price (Baht/ Avg. bar)

OIL = Crude Oil Price ($/Barrel)

FDI = Foreign Direct Investment (% of GDP)

BSI = Business Sentiment Index (Points)

DJIA = Dow Jones Industrial Average (Points)

CPI = Consumer Price Index (Points)

INT = Minimum Lending Rate (%)

CCI = Consumer Confident (Points)

I = Income (Baht)

AOR = 3 Months Advance Booking Rate (%)

e = Error term

Could illustrate by Figure 4.3;

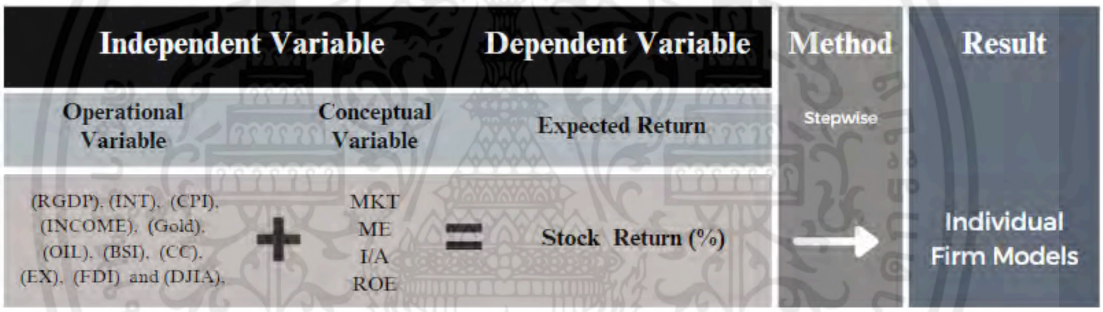

Figure 4.3 : Model Development Flow Chart

In the process of developing the Multifactor Model, we employ Multiple Linear Regression as our chosen data analytics method, incorporating an iterative refinement approach within its framework [Appendix 5B]. This involves systematically deducting independent variables with the highest P-values until only statistically significant factors remain. Computational tools are then employed to process the results, utilizing established statistical programs designed for research purposes. This methodology facilitates the development of individual models by identifying the significant independent variables tailored to each specific stock, thereby enhancing the efficacy of our analysis.

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4.6 Asset Allocation Strategy

The construction of our portfolio hinges on a carefully crafted asset allocation strategy designed to maximize the efficiency and effectiveness of our investments. This strategy adheres to the following criteria:

1) Max Information Ratio [Performance Measurement (4.7)]
2) Weighted less than 10%
3) Fully Investment
4) Liquidity Limit

Liquidity Limit is a crucial consideration, particularly in emerging markets such as Thailand. We evaluate the liquidity of each stock to ensure efficient buying and selling without causing substantial market impact.

We are adopting the **summation of daily trade values over the past three days** as a criterion for determining the investing weight of each stock. This strategic adjustment enhances our adaptability to dynamic market conditions, ensuring that our investment decisions align with recent trading activities. A higher amount indicates increased liquidity, providing investors with the advantage of more frequent buying and selling activities. This modification is intended to elevate our responsiveness to market dynamics, foster efficiency in trading, reduce transaction costs (including slippage costs), and afford improved market access for investors.

We intend to employ diverse criteria for constructing an Optimal Portfolio using Python as our primary tool, while utilizing Excel's Model Solver as a point of reference.

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4.7 Performance Measurement

To gauge the effectiveness and relative performance of our portfolio, we employ a robust performance measurement approach. This entails:

4.7.1 Benchmarking Against SET Total Return Index (SET TRI)

We evaluate the portfolio's performance by comparing it to the SET Total Return Index (SET TRI). This benchmark provides a valuable reference point, enabling us to assess the portfolio's returns in the context of the broader Thai equity market.

4.7.2 Performance Evaluation Through Ratio Analysis

We intend to assess the performance of existing portfolios through the use of ratios. The specific ratios for consideration encompass Sharpe Ratio, Treynor Ratio, Sortino Ratio, Jensen's Alpha, Tracking Error and Information Ratio to provide a comprehensive evaluation of their performance.

Sharpe Ratio

The Sharpe Ratio is commonly used to gauge the performance of an investment by adjusting for its risk.

Sharpe Ratio Formula

$$Sharpe\ Ratio\ =\ \frac{(R_p - R_f)}{StdDev\ R_x}$$

Where:

- R_p = Expected portfolio return
- R_f = Risk-free rate of return
- $StdDev\ R_x$ = Standard deviation of portfolio return (or, volatility)

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ไม่ว่ากรณีใดๆ ทั้งสิ้น อีกทั้งห้ามมิให้ดัดแปลงเนื้อหาและต้องอ้างอิงถึงเจ้าของเอกสารทุกครั้งที่มีการนำไปใช้

The higher the ratio, the greater the investment return relative to the amount of risk taken, and thus, the better the investment. The ratio can be used to evaluate a single stock or investment, or an entire portfolio.

Treynor Ratio

The Treynor Ratio is a portfolio performance measure that adjusts for systematic risk. In contrast to the Sharpe Ratio, which adjusts return with the standard deviation of the portfolio, the Treynor Ratio uses the Portfolio Beta, which is a measure of systematic risk.

Treynor Ratio Formula

$$Treynor\ Ratio\ =\ \frac{(R_p - R_f)}{B_p}$$

Where:

- R_P = Expected portfolio return
- R_f = Risk-free rate of return
- B_P = Beta of the Portfolio; A measurement of its volatility of returns relative to the entire market.

A higher ratio indicates a more favorable risk/return scenario.

Sortino Ratio

The Sortino ratio is a risk-adjustment metric used to determine the additional return for each unit of downside risk. It is computed by first finding the difference between an investment's average return rate and the risk-free rate. The result is then divided by the standard deviation of negative returns.

Sortino Ratio Formula

$$Sortino\ Ratio\ =\ \frac{(R_P - R_f)}{MSD_{min}}$$

Where:

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- R_p = Expected portfolio return
- R_f = Risk free rate of return
- MSD_{min} = Standard deviation of Negative Return (Downside)

Ideally, a high Sortino ratio is preferred, as it indicates that an investor will earn a higher return for each unit of a downside risk.

Jensen's Alpha

Jensen's alpha is a formula used to calculate an investment's risk-adjusted value. Also referred to as Jensen's Performance Index and ex-post alpha, Jensen's alpha aims to determine the abnormal return of a portfolio or security.

Jensen's Alpha Formula

$$Jensen's\ alpha = R_p - [R_f + B_p * (R_m - R_f)]$$

Where:

- R_P= Expected portfolio return
- R_f = Risk-free rate of return
- B_P = Beta of the Portfolio; A measurement of its volatility of returns relative to the entire market.

Alpha value can be positive or negative with higher positive values suggesting better asset performance compared to expectations and negative values indicating that the asset performed worse than expected.

Tracking error

Tracking error is a measure of financial performance that determines the difference between the return fluctuations of an investment portfolio and the return fluctuations of a chosen benchmark. The return fluctuations are primarily measured by standard deviations.

Tracking error formula

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$$Tracking\ Error\ =\ \sqrt{\frac{\sum_{i=1}^{n}(R_p - R_f)^2}{N-1}}$$

Where:

- R_p = Expected portfolio return
- R_f = Risk Free (Benchmark's) Return
- N = Number of Return Periods

Tracking error is an indicator of a manager's skill and a reflection of how actively or passively a portfolio is managed. Actively managed portfolios seek to provide above-benchmark returns, and they generally require added risk and expertise to do so. In these cases, the investor seeks to maximize tracking error. On the other hand, passively managed portfolios seek to replicate index returns, and so a large tracking error is generally considered undesirable for these investors.

Information Ratio

The information ratio measures the risk-adjusted returns of a financial asset or portfolio relative to a certain benchmark. This ratio aims to show excess returns relative to the benchmark, as well as the consistency in generating the excess returns.

Information Ratio formula

$$Information\ Ratio\ =\ \frac{(R_p - R_b)}{TE}$$

Where

- R_p = Expected portfolio return
- R_b = Benchmark's Return
- TE = Tracking Error (S.D. of portfolio returns from the returns of a benchmark)

The higher information ratios indicate a desired level of consistency, whereas low information ratios indicate the opposite.

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By conducting these performance measurements, we ensure transparency and accountability in assessing the effectiveness of our portfolio strategy and its ability to meet our risk-adjusted return objectives.

4.8 Rebalance Portfolio

In our risk management strategy, we adopt a rebalancing approach designed to effectively address potential risks. This method involves two distinct strategies: Calendar-based and Threshold-based rebalancing . While the Calendar-based approach entails scheduled adjustments at regular intervals (e.g., quarterly), the Threshold-based method responds to deviations from target allocations by initiating rebalancing actions [Appendix 6B].

Threshold-Base Rebalancing

- Sell Stock if Loss Reaches 20%: As part of our portfolio risk control measures, if a stock experiences a loss of 20%, we implement a proactive strategy. We divest from the underperforming stock and reallocate the capital into stocks that exhibit consistent upward momentum, as evidenced by trading above their EMA90 trend lines.

- Absolute Monthly VaR at 95% Below 10% of Portfolio: Our risk management strategy involves a commitment to maintaining Absolute Value at Risk (VaR) at 95% confidence levels below -10% of the portfolio's value. Should VaR exceed this threshold, we reallocate assets to ensure that the portfolio remains within acceptable risk parameters.

- If Portfolio Loss Hits 10%, Sell All: Upon reaching a 10% cumulative loss, the entire portfolio is sold as a precautionary measure to prevent further losses. This approach offers a safeguard and allows for reassessment before reinvestment.

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Calendar-Base Rebalancing

A quarterly rebalancing strategy involves adjusting the portfolio regularly to maintain the desired asset allocation and risk tolerance. By systematically reviewing and realigning the holdings every three months, this approach aims to capitalize on market fluctuations, prevent overconcentration, and promote a balanced and resilient investment portfolio over time.

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Chapter 5
Results and Discussion

Within this section, a comprehensive breakdown of the outcomes obtained at each procedural stage is presented, as shown in Figure 5.1.

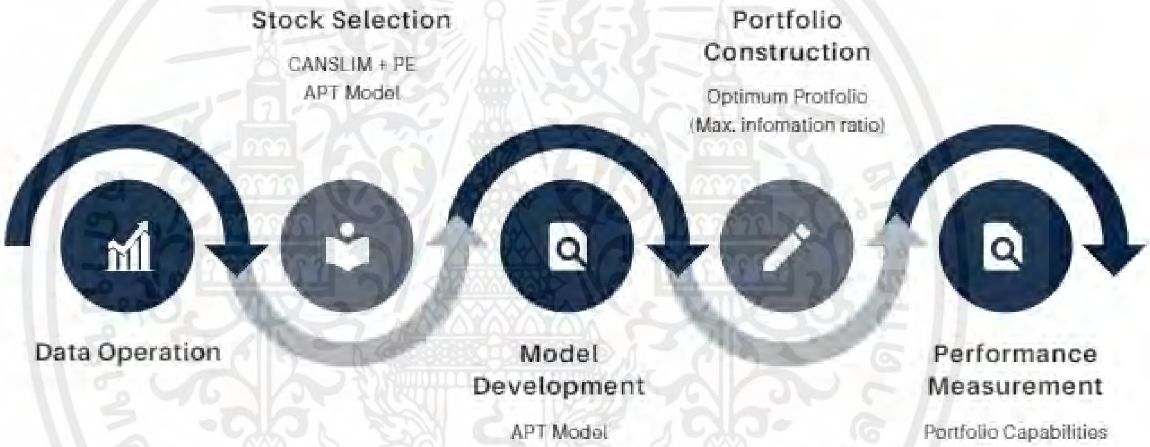

Figure 5.1: Outcome Summary of Each Process

Through an extensive exploration of the Thai Equity Market, our analysis covered a comprehensive spectrum of 99 stocks listed in the SET100 as of October 31, 2023 [Appendix 1.1C and 1.2C]. This thorough examination encapsulated all relevant factors associated with each stock, providing a holistic understanding of the market landscape and its contributing elements. Data were collected from various sources, including abbreviations, tickers, and secondary sources, with the capability to retrieve real-time data from website APIs for further validation, as illustrated in Table 5.1.

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Source	Ticker	Name
Bloomberge	TRI	Total Return index
	PX_LAST	Last Price
	CUR_MKT_CAP	Market Cap
	PE_Ratio	PE Ratio
	PX_Volumn	Trading Volumn
	BS_SH_OUT	Outstanding Share
	RETURN_COM_EQY	ROE
	SET100 INDEX	SET100
	GVTL10YR INDEX	RISK FREE RATE
	THG PQQ INDEX	REAL GDP QoQ
	THCPIYOY	Consumer price index
	THCCI INDEX	Consumer Confidence Index
	THGOBRSL INDEX	Gold bar price
	USCRWTIC	Crude oil price
	THBSI INDEX	Business Sentiment Index
	THFDITTL	Foreign Direct Investment
	INDU INDEX	Dow Jone Index
	USDTHB CURNCY	Exchange rate THB/usd
	THWGTL INDEX	Aveage Labor Costs
Bank of Thailand	FM_RT_001_S2	Minimum Leanding Rate
	EC_EI_028_S2	3-Month Advance Booking Rate
Yahoo! Finance Finnomena	Website tracking APIs.	

Table 5.1: List of Data Collected from Various Sources

Following data collection, we conducted an analysis to assess the economic factor risks and the associated risk premiums using the Ordinary Least Square Method. Moreover, we employed the Arbitrage Pricing Theory (APT) model to estimate the expected returns of securities and determine the required return for investment decision-making. The outcomes of the study are outlined as follows:

5.1 The Data Operation

5.1.1 Data Stationary

Initiating the Assessment of Data Stationarity, our initial step involved conducting the Augmented Dickey-Fuller Test (ADF Test) on our raw data using Python. Our findings revealed that the majority of factors remain statistically insignificant (non-stationary), as illustrated in Table 5.2 below.

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	Factors:	ADF-Statistic:	P-Value:	Stationary of Data	Number of lags:	Number of observations:
0	Market Risk Premium	-8.415539	0.0000	Stationary	0.0	40.0
1	Market share	-1.981134	0.2949	Non-Stationary	7.0	33.0
2	Investment	-6.932496	0.0000	Stationary	0.0	40.0
3	Profit	-2.944375	0.0404	Stationary	7.0	33.0
4	Consumer Price Index	-2.005940	0.2840	Non-Stationary	5.0	35.0
5	Real GDP	-7.953045	0.0000	Stationary	0.0	40.0
6	Consumer Confidence Index	-1.173133	0.6850	Non-Stationary	1.0	39.0
7	Gold Bar Price	0.259343	0.9754	Non-Stationary	0.0	40.0
8	Crude Oil Price	-2.358823	0.1537	Non-Stationary	0.0	40.0
9	Business Sentiment Index	-3.308096	0.0145	Stationary	0.0	40.0
10	Foreign Direct Investment	-6.520938	0.0000	Stationary	0.0	40.0
11	Dow Jone Industrial Average	-0.739536	0.8362	Non-Stationary	0.0	40.0
12	Interest Rate Policy	-1.580267	0.4935	Non-Stationary	2.0	38.0
13	Exchange Rate	-2.124060	0.2350	Non-Stationary	0.0	40.0
14	Thai Wage	0.609306	0.9878	Non-Stationary	7.0	33.0
15	AOR	-1.939517	0.3137	Non-Stationary	4.0	36.0

Table 5.2: Result from Testing Stationary in Raw data

To address potential issues related to strong trends or seasonality in our time series data, we proceeded to transform the data into percentage changes. Upon completing this transformation, the resulting outcomes are detailed as Table 5.3 below.

	Factors:	ADF-Statistic:	P-Value:	Number of lags:	Stationary of Data	Number of observations:
0	Market Risk Premium	-8.364807	0.0000	0	Stationary	40.0
1	Firm Size (ME)	-4.369686	0.0003	1	Stationary	39.0
2	Investment	-6.932496	0.0000	0	Stationary	40.0
3	Profit	-2.944375	0.0404	7	Stationary	33.0
4	RGDP	-7.953045	0.0000	0	Stationary	40.0
5	Exchange Rate	-7.568282	0.0000	0	Stationary	40.0
6	Gold Bar Price	-6.805835	0.0000	0	Stationary	40.0
7	Crude Oil Price	-8.064828	0.0000	0	Stationary	40.0
8	Foreign Direct Investment	-10.569843	0.0000	0	Stationary	40.0
9	Business Sentiment Index	-8.134504	0.0000	0	Stationary	40.0
10	Dow Jone Industrial Average	-8.099247	0.0000	0	Stationary	40.0
11	Consumer Price Index YoY	-6.102862	0.0000	0	Stationary	40.0
12	Interest Rate Policy	-3.585674	0.0060	9	Stationary	31.0
13	Consumer Confidence Index	-4.942055	0.0000	0	Stationary	40.0
14	Thai Wage	-4.704523	0.0001	2	Stationary	38.0
15	AOR	-6.803126	0.0000	1	Stationary	39.0

Table 5.3: Result from Testing Stationary after Transform to %Change

The results demonstrate the suitability of the data for modeling in subsequent steps.

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ไม่ว่ากรณีใดๆ ทั้งสิ้น อีกทั้งห้ามมิให้ดัดแปลงเนื้อหาและต้องอ้างอิงถึงเจ้าของเอกสารทุกครั้งที่มีการนำไปใช้

5.1.2 Factors Correlation

In the Correlation Test, we employed Python code to analyze the relationships among factors and visualize them using a heatmap. The resulting analysis is presented in Figure 5.2 below.

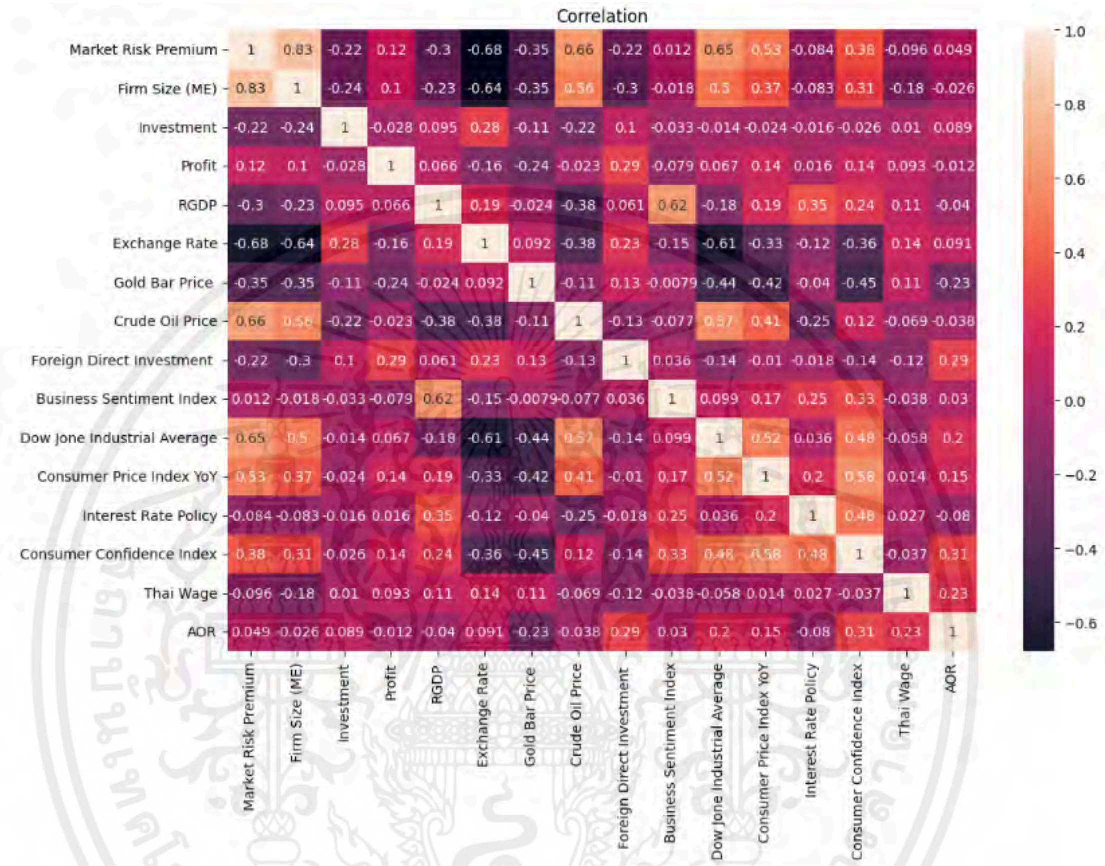

Figure 5.2: Factors Correlation Heatmap

The heatmap reveals that no factors exhibit high correlations, with all values falling below 0.7 or above -0.7. This indicates that the data is suitable for model development, as it mitigates the risk of multicollinearity. Therefore, there is no need to remove any factors.

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5.1.3 Incorporating Lag Terms

Our approach entails selecting the appropriate lag term tailored to the characteristics of the data, aiming to enhance predictive accuracy while mitigating issues of overfitting or underfitting in the model. Upon conducting our research, a notable challenge emerged: variations in declaration dates. To address this, we designated a lag of 0 for daily transaction data. Additionally, we observed that certain factors inherently exhibit lag in their data nature, obviating the need for further lag incorporation. For instance, metrics such as Market Equity (ME), Investment to Assets (IA), and Return on Equity (ROE), sourced from financial reporting, typically undergo announcements midway through the quarter, naturally embodying a lag effect.

Similarly, indicators such as the Business Sentiment Index (BSI) and Consumer Confidence Index (CCI), reliant on economic reports from the Bank of Thailand (BOT), are usually released in the 5th day after the month-end and second week following the month-end respectively, reflecting data from the preceding month. This temporal delay inherently introduces a lag effect into the data, necessitating careful consideration during the modeling process. Consequently, no additional lag terms were deemed necessary for most factors.

However, one factor stood out in terms of its significance in lag terms: the '3-Months Advance Booking Rate.' This factor's relevance is particularly pronounced in sectors such as tourism, travel, and hotel, where its impact is felt after a three-month period. As a result, we have determined that incorporating a lag of 1 for this factor will be instrumental in refining our model for subsequent development stages, all of the assumptions are further detailed in Table 5.4 below.

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Concept	Factor	Definition	Date Declaration	Operation	Final Lag	Note
CAPM	MKT	Market Return	Daily Transaction Data [Close Price]	%Change	0	
Q-Factor	ME	Firm Size - Book Value	Financial Reporting Dates (M2W2).	%Change [Dlog(X)]	0	Inherently encompasses its own lag
	IA	Investment over the Assets	Financial Reporting Dates (M2W2).	0	0	
	ROE	Return On Equity	Financial Reporting Dates (M2W2).	0	0	
Arbitrage Pricing Model	RGDP	Real GDP Growth	Quarterly RGDP Previous Quarter (M2W2)	%Change	0	
	EX	Exchange Rate	Daily Transaction Data [Close Price]	%Change	0	
	Gold	Gold Bar Price	Daily Transaction Data [Close Price]	%Change	0	
	Oil	Oil Price	Daily Transaction Data [Close Price]	%Change	0	
	DJIA	Dow Jones Index	Daily Transaction Data [Close Price]	%Change	0	
	FDI	Foreign Direct Investment	Quarterly Report for Previous Quarter (Last Day of the Subsequent Quarter).	%Change [From Average]	0	Inherently encompasses its own lag
	BSI	Business Sentiment Index	Economic Report for the Previous Month (Released on the 5th day after the month-end).	%Change	0	
	CPI	Inflation YoY	Economic Report for the Previous Month (Released on the 5th day after the month-end).	%Change	0	
	I	Minimum Lending Rate : MLR	Monthly Report (delay 10 days)	%Change	0	
	CCI	Consumer Confidence Index	Economic Report for the Previous Month (Released on the second week after the month-end).	%Change	0	
	W	Average Labor Costs	3 Month Average in quarter (Delay 1 Quarter).	%Change	0	
	AOR	3-Month Advance Booking Rate	Before 3 Month (delay 1 month).	%Change	-1	
Risk Free			T-Bill 1 month (Lowest Return)			**At 30/09/2023**

Table 5.4: Assumption of lag in Each Factors

5.2 Stock Selection

5.2.1 CANSLIM + PE

After calculating the scores using the CANSLIM + APT model in Python [Appendix 1D], we created a new column called 'Ranking' and sorted the stocks from lowest to highest. The results are depicted in Table 5.5 below. Subsequently, we will proceed to use the top 50 stocks to construct individual APT models in subsequent steps.

	rank C	rank A	rank N	rank S	rank L	rank I	rank M	Total Rank	Rank
INTUCH	40.0000	20.0000	5.0000	2.0000	6.0000	99.0000	38.0000	118.6154	1.0000
DELTA	29.0000	21.0000	6.0000	23.0000	24.0000	68.0000	23.0000	131.2308	2.0000
VGI	19.0000	10.0000	92.0000	3.0000	11.0000	96.0000	13.0000	155.3846	3.0000
TOP	1.0000	1.0000	44.0000	55.0000	54.0000	14.0000	3.0000	159.0769	4.0000
CBG	28.0000	34.0000	22.0000	29.0000	37.0000	86.0000	16.0000	172.6154	5.0000
BCP	2.0000	6.0000	13.0000	70.0000	84.0000	5.0000	2.0000	177.3846	6.0000
CHG	38.0000	24.0000	30.0000	9.0000	47.0000	57.0000	25.0000	177.3846	6.0000
MEGA	25.0000	55.0000	11.0000	21.0000	31.0000	23.0000	41.0000	185.7692	8.0000
PLANB	43.0000	17.0000	45.0000	30.0000	34.0000	40.0000	17.0000	189.0769	9.0000
ACE	17.0000	54.0000	58.0000	10.0000	4.0000	41.0000	44.0000	190.1538	10.0000
BH	31.0000	22.0000	3.0000	4.0000	95.0000	46.0000	36.0000	194.5385	11.0000
PTT	15.0000	7.0000	55.0000	43.0000	46.0000	19.0000	32.0000	199.4615	12.0000
NEX	79.0000	4.0000	8.0000	53.0000	22.0000	81.0000	30.0000	202.2308	13.0000
OSP	13.0000	9.0000	33.0000	17.0000	59.0000	77.0000	68.0000	204.9231	14.0000
ADVANC	42.0000	19.0000	2.0000	82.0000	20.0000	18.0000	39.0000	205.3846	15.0000
ORI	49.0000	27.0000	14.0000	65.0000	16.0000	8.0000	35.0000	206.6154	16.0000
OR	95.0000	3.0000	52.0000	36.0000	1.0000	73.0000	18.0000	210.6154	17.0000
HANA	61.0000	14.0000	41.0000	7.0000	78.0000	12.0000	9.0000	210.9231	18.0000
TQM	70.0000	44.0000	4.0000	22.0000	15.0000	70.0000	59.0000	219.3846	19.0000
AOT	6.0000	92.0000	61.0000	25.0000	10.0000	93.0000	19.0000	220.1538	20.0000
BDMS	32.0000	30.0000	25.0000	13.0000	75.0000	49.0000	43.0000	221.7692	21.0000
MBK	16.0000	2.0000	65.0000	57.0000	76.0000	32.0000	7.0000	225.4615	22.0000
PTTEP	36.0000	57.0000	29.0000	27.0000	14.0000	17.0000	62.0000	226.3077	23.0000
CKP	5.0000	61.0000	84.0000	28.0000	42.0000	79.0000	1.0000	227.0769	24.0000
SPRC	3.0000	88.0000	60.0000	18.0000	28.0000	24.0000	29.0000	227.8462	25.0000
STGT	86.0000	12.0000	90.0000	6.0000	17.0000	89.0000	11.0000	228.8462	26.0000
SNNP	45.0000	31.0000	15.0000	16.0000	66.0000	76.0000	55.0000	233.8462	27.0000
SCGP	9.0000	58.0000	77.0000	33.0000	5.0000	74.0000	48.0000	235.6923	28.0000
AP	23.0000	26.0000	23.0000	37.0000	81.0000	6.0000	46.0000	236.4615	29.0000
BCH	18.0000	91.0000	48.0000	8.0000	48.0000	67.0000	20.0000	238.1538	30.0000
CPN	22.0000	18.0000	20.0000	63.0000	80.0000	39.0000	34.0000	240.0000	31.0000
MTC	39.0000	40.0000	21.0000	86.0000	13.0000	53.0000	40.0000	243.0769	32.0000
BCPG	14.0000	52.0000	76.0000	47.0000	39.0000	60.0000	12.0000	244.6154	33.0000
GPSC	91.0000	5.0000	86.0000	49.0000	3.0000	91.0000	5.0000	246.0000	34.0000
THG	27.0000	59.0000	54.0000	42.0000	50.0000	82.0000	14.0000	252.3077	35.0000
KCE	46.0000	56.0000	34.0000	12.0000	82.0000	34.0000	22.0000	254.6154	36.0000
KTC	41.0000	42.0000	10.0000	68.0000	33.0000	51.0000	60.0000	257.9231	37.0000
HMPRO	52.0000	45.0000	7.0000	56.0000	36.0000	35.0000	61.0000	259.6923	38.0000
CPALL	24.0000	28.0000	26.0000	66.0000	58.0000	63.0000	53.0000	259.8462	39.0000
WHA	76.0000	11.0000	24.0000	50.0000	70.0000	27.0000	27.0000	260.0769	40.0000
JMT	50.0000	43.0000	62.0000	14.0000	40.0000	85.0000	50.0000	265.5385	41.0000
GULF	63.0000	8.0000	32.0000	74.0000	23.0000	84.0000	64.0000	270.4615	42.0000
BEM	20.0000	32.0000	56.0000	69.0000	57.0000	75.0000	31.0000	270.7692	43.0000
SAWAD	37.0000	29.0000	16.0000	79.0000	71.0000	30.0000	42.0000	276.3077	44.0000
GLOBAL	47.0000	63.0000	40.0000	20.0000	25.0000	55.0000	79.0000	278.2308	45.0000
TCAP	34.0000	15.0000	53.0000	41.0000	88.0000	48.0000	45.0000	279.6923	46.0000
AWC	57.0000	36.0000	70.0000	34.0000	8.0000	56.0000	71.0000	280.3077	47.0000
DOHOME	90.0000	13.0000	85.0000	62.0000	2.0000	92.0000	24.0000	283.0769	48.0000
CK	7.0000	37.0000	72.0000	80.0000	87.0000	2.0000	10.0000	293.1538	49.0000
TIDLOR	33.0000	38.0000	31.0000	76.0000	62.0000	47.0000	51.0000	294.6154	50.0000

Table 5.5: Top 50 Stocks ranking by CANSLIM + PE scoring approach

5.2.3 Multifactor Model Development

At this stage, we performed Stepwise Elimination OLS in Python [Appendix 2D], where we systematically removed non-significant factors based on their P-values, retaining only the significant ones for each security [Appendix 2C] , while simultaneously addressing model problems such as Multicollinearity, Heteroscedasticity, and Serial Correlation [Appendix 3C]. This process ensured that only the factors deemed statistically significant remained in the model for each security, as illustrated in Table 5.6 below.

Sector	Stock	MKT	ME	IA	ROE	RGDP	EX	Gold	Oil	FDI	BSI	DJIA	CPI	I	CCI	W	AOR
AGRI-BUSINESS	STA	2.7314											-0.0103				
AUTOMOTIVE	NEX				-0.0129			-2.3742									
BANKING	SCB	1.6008					1.1614					0.4846			0.4344		
	KBANK	1.389				0.0233	0.9513					0.593		-0.1532	0.5649		
	BBL	0.6689				0.0162		0.4155							0.6946		
	KTB	0.4301				0.0189									0.6982		
	TTB	0.7713													0.925		
	TISCO	0.8068				0.0163					0.001						
	TCAP	0.8067		-10.6622		0.0121			-0.1681	0.000009283		0.4981			0.5909	2.4705	
	KKP	0.8939	14.8612			0.0223								-0.2318	0.5452		
COMMERCE	CPALL	0.7326								0.00001081							
	CRC																
	HMPRO	1.2294								0.00001748						1.484	
	GLOBAL	1.5318				-0.0403					0.0015						
	COM7	2.5985	4.5759			-0.0724					0.003						
	DOHOME																
	MEGA	1.8674		3.7133			1.8008										
	SABUY																
CONSTRUCT MATERIAL	SCC	0.6718															
	TASCO		18.2415	1.2625					-0.3701								
CONSTRUCT SERVICES	CK	0.8312	-3.7882		0.0044							-0.5064				3.3803	
	STEC	1.9515					1.6506		-0.1833				-0.0053		0.7668	4.2832	
ELECTRNC COMPONENTS	DELTA			8.5358			-5.0666			-0.00008403		2.8463		-1.0606			0.0714
	KCE	1.957				-0.0611	2.9399		-0.3619	-0.00005371	0.0049						-0.03
	HANA					-0.0626		-2.2096			0.0024						

Sector	Stock	MKT	ME	IA	ROE	RGDP	EX	Gold	Oil	FDI	BSI	DJIA	CPI	I	CCI	W	AOR
ENERGY & UTILITIES	PTT	1.234									0.0008						
	PTTEP	1.6878		1.0383							0.0008						
	GULF	1.1352				0.023		1.4829		0.0000175							
	OR																
	EA	2.1225								0.00001911			-0.0076		1.4185	6.9969	
	GPSC	1.3684			0.0093												
	TOP	1.3284			-0.0059	0.0258		-0.7775			0.0022						
	BGRIM						-2.3983				0.0012	-0.6772					
	BANPU	1.4265				0.0228			0.1872	-0.00003237	0.0018			-0.2111		-2.5086	
	RATCH	0.5801															
	EGCO	0.7468			0.0027												
	BCP	1.6822					1.5542		-0.1504		0.0011						
	IRPC	1.1925				0.0263			-0.2447	-0.00002834	0.0013	0.9234		-0.3272		-2.6007	
	SPRC	1.7987								-0.00002088	0.0018						
	CKP	1.6447				-0.0392			0.2276		0.0013						
	BCPG	2.1202											-0.0036	0.2344		5.5829	
	GUNKUL	1.2541			0.0075			-0.9568	-0.2415	0.00002779	-0.0026	0.7664		-0.2506		2.8764	
	PTG	1.3144	23.1805														
	ACE																
FASHION	AURA																
FINANCE/SEC	KTC	1.0764			0.005			-1.4573									
	MTC	0.9985	13.8561					-1.323									
	TIDLOR																
	SAWAD						-2.5249	-2.0595			0.0019						
	JMT	1.7664				-0.0529					0.0026						
	BAM																
	BYD	2.6341			-0.0331					0.00009863	-0.0091						
	THANI						-2.0267		0.3637								

Sector	Stock	MKT	ME	IA	ROE	RGDP	EX	Gold	Oil	FDI	BSI	DJIA	CPI	I	CCI	W	AOR
FOOD/BEVERAGE	CPF	0.8247						0.8008				-0.4034					
	CBG	1.829	16.9285			-0.0377					0.0021	-1.2787					
	TU			2.8476													
	OSP						-1.9311						0.0021	0.1634	-0.9455	2.2335	
	BTG																
	SNNP																
HEALTHCARE SERVICE	BDMS	0.6999	9.6729														0.0125
	BH	0.8314		-3.607			1.543	-0.7725	-0.3785			1.2715				2.5018	0.0272
	BCH	1.242								0.00001651						2.9886	
	THG	1.1749			0.0286				-0.9068		-0.0037	3.3801		-0.6368			
	CHG	0.6746														3.3319	
INFO & COMM TECH	ADVANC	0.4901	3.4647									0.4363					
	INTUCH	0.6995	3.0647					0.6291									
	TRUE																
	SIRI	1.4886			0.0035												
	FORTH	1.4753			0.0031		3.3949								-0.7969		
INSURANCE	TLI																
	AP	1.7549				-0.0202			-0.1955		0.0019						
	TIPH																
	TQM			3.7254		-0.053	-4.8835				0.0044	-1.2503	0.0108		-2.6392	-7.4952	
MEDIA & PUBLISHING	PLANB					-0.0481			-0.7683		0.0029		0.0081				
	VGI	1.2547															
PACKAGING	SCGP																
PERS PRODCT & PHARM	STGT																
PETROCHEM & CHEM	PTTGC	1.6587									0.0009					-2.8948	
	IVL	1.5585	10.7413														

Sector	Stock	MKT	ME	IA	ROE	RGDP	EX	Gold	Oil	FDI	BSI	DJIA	CPI	I	CCI	W	AOR
PROPERTY DEV	AWC																
	LH	0.7967		-0.6505	0.0019												
	WHA	1.2476	1.4769								0.0009				0.5546		
	SPALI	1.2259											-0.0046		0.7509	3.2296	
	BLA	0.9656															
	MBK	0.7271						-0.8064			0.0009						
	AMATA	1.7376									0.0012						
	JMART	4.0872				-0.0533	3.545				0.0028						
	ORI	1.6238									0.0016						
TOUR & LEISURE	MINT	1.1398						-0.8624			0.0013						-0.0154
	CENTEL	1.6497					1.8611										
	ERW	1.65									0.0013						
TRANS & LOGIST	AOT	0.3947			0.0029				-0.1184				0.0032			1.9931	
	BEM	0.3838			0.0045							-0.4028	0.0022				
	BTS	0.581									0.0007	-0.4435					
	SJWD	1.0535															
	AAV	1.3634									0.0011	-0.8678					
	RCL	2.109	24.496		-0.0047					-0.00005427	0.0029	1.9072					
	PSL	2.8077													-1.302		

Table 5.6: Multifactor Model for Individual Stocks

The study revealed a diverse range of factors affecting individual securities' performance across various industry segments. Some securities lacked robust models or significant factors, mainly due to limited sample sizes, highlighting the challenge of constructing reliable models for such cases. For example, the ELECTRONIC COMPONENT sector displayed non-significant results in Market Risk, possibly due to abnormal fluctuations. Additionally, DELTA results indicated a stronger correlation with DJIA than SET, further emphasizing the significance of Market Risk in influencing most securities. However, among those analyzed, the Market Risk Premium emerged as the most influential factor, significantly impacting 72 out of the 99 securities studied from the SET100, underscoring the enduring relevance of classical financial models in contemporary investment analysis.

Furthermore, the Business Sentiment Index (BSI) and Real Gross Domestic Product (RGDP) held considerable sway, with 34 and 21 securities respectively showing significant correlations. This underscores the vital role of economic sentiment and macroeconomic indicators in driving market behavior. Positive shifts in business sentiment and real GDP growth often lead to increased investor confidence, driving stock prices higher.

Additionally, the strong correlation between the Consumer Confidence Index (CCI) and the BANKING sector highlights the positive impact of growing consumer confidence on stock prices. This aligns with the assumption that rising consumer confidence has diverse effects on stock performance, including heightened loan demand, increased deposit growth, greater investment activity, and enhanced credit quality.

Moreover, strong positive correlations observed between sectors like PROPERTY & DEVELOPMENT and ENERGY & UTILITIES with the Business Sentiment Index (BSI) provide further support for the idea that investor sentiment reflects broader economic trends. This can be attributed to the inherent nature of these sectors, which are closely intertwined with overall economic performance.

เอกสารนี้เป็นเอกสารที่สงวนไว้สำหรับการใช้งานเพื่อการศึกษาเท่านั้น ไม่อนุญาตให้นำไปใช้ประโยชน์ด้านการค้า ไม่ว่ากรณีใดๆ ทั้งสิ้น อีกทั้งห้ามมิให้ดัดแปลงเนื้อหาและต้องอ้างอิงถึงเจ้าของเอกสารทุกครั้งที่มีการนำไปใช้

Conversely, the study found a notable negative correlation between Oil Prices and sectors directly linked to the oil industry, suggesting that higher oil prices could lead to increased operating costs for these sectors, exerting downward pressure on their performance. However, this negative correlation was offset by a positive relationship within the Energy Sector itself, particularly in sectors related to electrical energy and gas, exemplified by companies like BANPU and CKP. This underscores the complex dynamics at play, emphasizing the need for a comprehensive understanding of market dynamics.

Additionally, strong links found between sectors like CONSTRUCTION SERVICE and HEALTHCARE SERVICE and Average Labor Cost suggest that higher wages can lead to increased demand and purchasing power in these industries. This supports the idea that rising average monthly wages in Thailand can positively impact stock prices by encouraging increased spending, thereby potentially making companies more profitable. Furthermore, companies like BDMS and BH in the HEALTHCARE SERVICE sector were connected with the 3-months Advance Booking Rate (AOR), predicting positive performance for an additional 3 months due to the value they offer to international tourists as their target customer segment.

Lastly, significant negative correlations between the Dow Jones Index and the TRANSPORTATION & LOGISTICS sector underscore how global market dynamics can impact local industries, reinforced by concerns regarding Thailand's infrastructure and domestic market.

In summary, these findings emphasize the complex array of factors shaping security performance, highlighting the need for a nuanced, data-driven approach to investment decision-making in today's dynamic financial landscape. Each security possesses a unique set of influencing factors, underscoring the importance of tailored investment strategies that account for specific nuances rather than relying solely on industry-wide trends.

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5.2.3 Arbitrage Pricing Theory

Based on Figure XX, to look for Arbitrage Opportunities with the APT Model, We compare the Required Rate of Return with the 10-Year Average Historical Return. If the Required Return is higher than the Historical Return, we consider adding the stock to our portfolio . This analysis was conducted using Python [Appendix 4C and 3D], and the results are summarized in Table 5.7.

Stock	Require Return	10 Y Hist Return	Result
DELTA	0.1339	0.1566	Reject
VGI	0.0311	-0.004	Accept
TOP	0.0667	0.024	Accept
CBG	0.0273	0.0586	Reject
BCP	0.1529	0.029	Accept
CHG	-0.0304	0.0502	Reject
MEGA	0.0255	0.0393	Reject
PLANB	-0.0936	0.047	Reject
ACE	0.0211	-0.0384	Accept
BH	0.0896	0.0442	Accept
PTT	0.0066	0.0185	Reject
NEX	0.032	0.0846	Reject
OSP	0.0655	0.0165	Accept
ADVANC	-0.001	0.013	Reject
ORI	0.0357	0.0724	Reject
OR	0.0211	-0.0473	Accept
HANA	0.0695	0.0621	Accept
TQM	0.1493	0.0963	Accept
AOT	0.0456	0.0448	Accept
BDMS	0.096	0.0232	Accept
MBK	0.0041	0.0193	Reject
PTTEP	0.0206	0.0282	Reject
CKP	-0.0363	0.0273	Reject
SPRC	0.1206	0.0376	Accept

Stock	Require Return	10 Y Hist Return	Result
STGT	0.0211	-0.1059	Accept
SNNP	0.0211	0.0997	Reject
SCGP	0.0211	0.0073	Accept
AP	0.0096	0.0072	Accept
BCH	0.0297	0.0422	Reject
CPN	0.0098	0.0179	Reject
MTC	0.2476	0.0548	Accept
BCPG	-0.0421	0.0218	Reject
GPSC	0.0044	0.0423	Reject
THG	0.0843	0.0679	Accept
KCE	0.0542	0.0873	Reject
KTC	0.0681	0.0919	Reject
HMPRO	0.003	0.0271	Reject
CPALL	0.0134	0.0209	Reject
WHA	0.0102	0.0379	Reject
JMT	0.0677	0.0779	Reject
GULF	0.058	0.0675	Reject
BEM	0.0883	0.0227	Accept
SAWAD	0.2865	0.0591	Accept
GLOBAL	0.0263	0.0287	Reject
TCAP	0.0413	0.0295	Accept
AWC	0.0211	-0.0072	Accept
DOHOME	0.0211	0.082	Reject
CK	-0.0393	0.0145	Reject
TIDLOR	0.0211	-0.0455	Accept

Table 5.7: Overall 50 Stocks filtered by Arbitrage Pricing Theory (APT) Model

In summary, we've identified 23 stocks that have passed the selection criteria of both CANSLIM + PE and APT models. These stocks are listed in Table 5.8.

Stocks			
ACE	AOT	AP	AWC
BCP	BDMS	BEM	BH
HANA	MTC	OR	OSP
SAWAD	SCGP	SPRC	STGT
TCAP	THG	TIDLOR	TOP
TQM		VGI	

Table 5.8: The remaining 22 stocks Result from using Arbitrage Pricing Theory (APT)

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5.2.4 Portfolio Construction

Stock	Weight	Average Return	Risk	Sharp Ratio
AOT	0.1000	0.1792	0.2265	0.6983
AP	0.1000	0.1948	0.3858	0.4504
BCP	0.0648	0.1160	0.3158	0.3007
BDMS	0.1000	0.0927	0.2113	0.3386
BEM	0.1000	0.0909	0.2081	0.3355
BH	0.1000	0.1769	0.2634	0.5914
HANA	0.0945	0.2485	0.4292	0.5297
OSP	0.0706	0.0658	0.2168	0.2063
SAWAD	0.0513	0.2364	0.4386	0.4908
SPRC	0.0678	0.1505	0.4245	0.3049
TCAP	0.0949	0.1179	0.2221	0.4359
THG	0.0162	0.2717	0.5902	0.4245
TQM	0.0366	0.3851	0.5642	0.6451

Table 5.9: Optimization Portfolio Allocation Result

After the meticulous selection of 22 stocks through the CANSLIM + PE and APT models, we proceeded to construct an optimized portfolio in Python [Appendix 4D], imposing predefined constraints. Remarkably, our analysis revealed that a mere 13 stocks were necessary to attain optimal Information Ratio, as shown in Table 5.9, a finding that aligns seamlessly with diversification theory. This strategic allocation facilitated the creation of a portfolio aligned with our objectives. Furthermore, we explored various portfolio configurations, including Maximum Return, Minimum Risk, Max Sharpe Ratio, and Max Dummy (Sharpe Ratio x Information Ratio), as delineated in Table 5.10, to gauge their comparative performance. Notably, the portfolio characterized by minimized risk demonstrated maximal diversification, in concordance with established diversification principles. While the Information Ratio was most pronounced in the portfolio with maximal informational inputs, alternative constructs such as Min Risk Max Sharpe and Dummy exhibited superior Return over Risk metrics. This underscores the efficacy of optimization methodologies in achieving desired outcomes. Ultimately, the determination of investment allocation is contingent upon desired returns and acceptable risk thresholds.

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Stock	Max Return	Min Risk	Max Sharpe	Max Information	Dummy
VGI					
TOP	0.0523	0.0214			
BCP	0.1000	0.1000		0.0648	0.0637
ACE					
BH	0.1000	0.1000	0.1000	0.1000	0.1000
OSP		0.1000	0.1000	0.0706	0.0961
OR					
HANA	0.1000	0.1000	0.1000	0.0945	0.1000
TQM	0.0366	0.0366	0.0366	0.0366	0.0366
AOT	0.1000	0.1000	0.1000	0.1000	0.1000
BDMS		0.1000	0.1000	0.1000	0.1000
SPRC	0.1000			0.0711	0.0160
STGT					
SCGP		0.1000	0.0710		
AP	0.1000	0.0092	0.0654	0.1000	0.1000
MTC	0.1000		0.0159		
THG	0.0162	0.0162	0.0162	0.0162	0.0162
BEM		0.1000	0.1000	0.1000	0.1000
SAWAD	0.1000	0.0217	0.1000	0.0513	0.0765
TCAP	0.0949	0.0949	0.0949	0.0949	0.0949
AWC					
TIDLOR					
SUM	1.0000	1.0000	1.0000	1.0000	1.0000
No. of Stock	12	14	13	13	13

Performance	Port1	Port2	Port3	Port4	Port5
Return (Y)	18.69%	13.86%	15.70%	16.16%	16.22%
Risk (Y)	25.50%	16.14%	17.80%	19.95%	19.06%
Sharpe Ratio	0.6501	0.7279	0.7637	0.7042	0.7404
Information Ratio	1.0137	0.9253	1.0384	1.2301	1.2040
Jensen's Alpha	0.1368	0.0824	0.7637	0.1083	0.1091

Table 5.10: Optimization Portfolio Comparison with other Allocation Strategies

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5.2.5 Portfolio Measurement

1. Portfolio Expected Return		
Return (Y)		0.1616
2. Portfolio Variance		
Port Variance (Y)		0.0398
Port S.D. (Y)		0.1995
3. Port S_p		0.7042
Risk Free (Y)		0.0211
4. Information Ratio		1.2301
5.Dummy (Sharpe * Information)		0.8663
6.PortFolio Beta		0.8339
7. Jensen Alpha		0.1083
8. Differential Return by SD (CML)		0.1046
9. Total Risk	0.0323	100.00%
Unsystematic Risk	0.0122	37.70%
Systematic Risk	0.0201	62.30%
10. Treynor Ratio		0.1685
11. Sortino Ratio		1.4959

Table 5.11: Portfolio Performance measurement

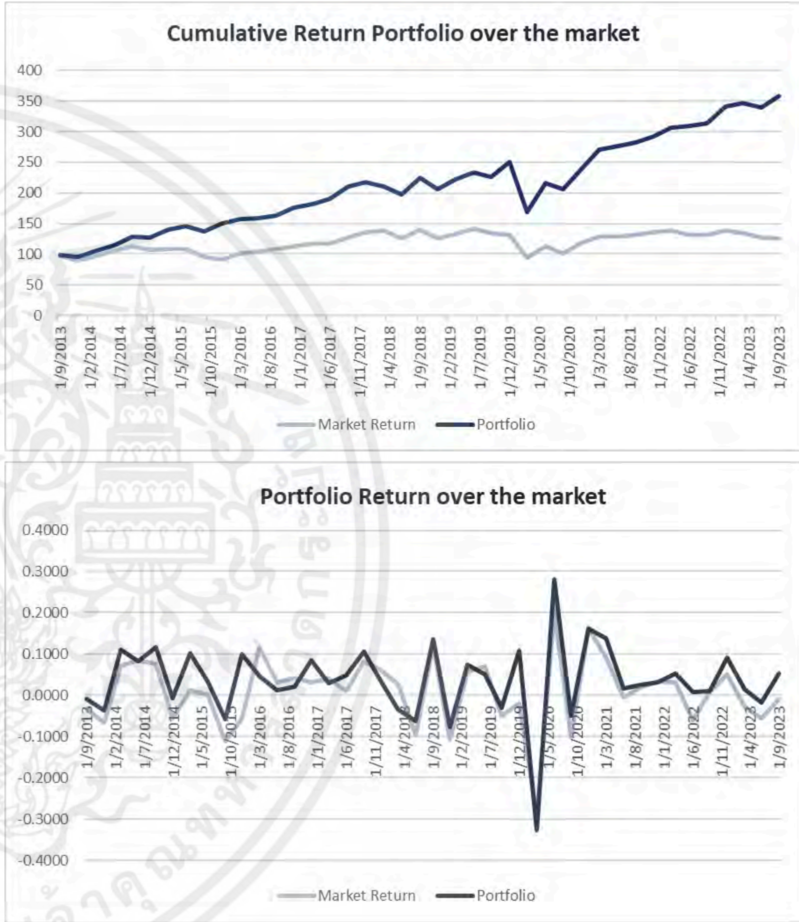

Figure 5.3: Portfolio Performance Over 10 Years Historical Data

Based on the data provided in Table 5.11, the Max Information Portfolio showcases compelling performance metrics. With an annual return of 16.16% and a corresponding risk level of 19.95% per annum, it demonstrates favorable investment potential. This performance is particularly noteworthy when compared to the T-Bill 1-month Risk-Free Rate, currently at 0.0211, indicating a Sharpe Ratio of 0.7042, surpassing the market average of 0.6202 units. Additionally, the Portfolio Beta, a measure of systematic risk, is calculated at 0.8339, resulting in a Treynor Ratio of 0.1685 and a Jensen's Alpha of 0.1083. Of significance is the Information Ratio,

Performance	Max Information Portfolio	Market Benchmark
Return (Y)	16.16%	3.79%
Risk (Y)	19.95%	17.01%
Sharpe Ratio	0.7042	0.084
Treynor Ratio	0.1685	0.017
Jensen's Alpha	0.1083	0
Information Ratio	1.2301	0

Table 5.12: Portfolio Performance Comparison with SET Market

In summary, the portfolio constructed through the CANSLIM + PE and APT strategies exhibits enhanced performance compared to the market average. As illustrated in Figure 5.3, further analysis of cumulative returns over the past decade reveals that investing in stocks selected through these strategies results in a growth of 3.57 times compared to the initial investment, significantly outpacing the market's growth of only 1.26 times. These findings underscore the efficacy of employing CANSLIM + PE and APT screening methods in achieving favorable portfolio outcomes.

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Chapter 6
Conclusion and Recommendation

6.1 Project Summary

Our study delves into the intricate dynamics of individual security returns, revealing the influence of diverse factors unique to each asset. By integrating the CANSLIM + PE and APT methodologies in portfolio construction, investors can adeptly navigate market complexities, seizing growth opportunities while mitigating risks effectively. This holistic approach not only enhances potential stock appreciation but also aims to outperform passive investment strategies, surpassing market benchmarks in cumulative returns.

In summary, the fusion of CANSLIM + PE and APT frameworks presents a promising strategy for optimizing portfolios amidst the evolving equity landscape. While acknowledging the inherent variability in security returns, leveraging established models like CAPM provides a sturdy foundation for informed investment decisions, emphasizing that there's no one-size-fits-all model, even within similar industry sectors.

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Moreover, employing APT through the Stepwise OLS method has refined the identification of significant factors for each stock, yielding more precise estimates of required returns. Grouping stocks by industry has further enriched our insights. For instance, BANKING stocks exhibit positive correlations with Real GDP and Consumer Confidence Index, while PROPERTY DEVELOPMENT, and ENERGY sectors respond positively to BSI. Conversely, oil prices show a clear inverse impact on oil-related businesses. Additionally, stocks in CONSTRUCTION and HEALTHCARE services exhibit positive correlations with average labor costs. Notably, the Dow Jones Index demonstrates negative significance for TRANSPORTATION & LOGISTICS sectors.

Furthermore, the implementation of optimization portfolios has facilitated the effective achievement of our investment objectives. Despite market complexities, adopting a holistic approach to portfolio management equips investors with a robust strategy to navigate uncertainties and pursue sustained growth.

In conclusion, our study underscores the significance of embracing dynamic strategies like CANSLIM + PE and APT in portfolio construction. This tailored approach empowers investors to optimize returns while prudently managing risks in today's dynamic financial landscape.

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6.2 Recommendation

Based on the findings of the study, the following recommendations are proposed:

1. Data Extension: Expanding the dataset used for analysis can significantly enhance the accuracy of the model. By incorporating additional data sources or extending the historical timeframe, researchers can capture a more comprehensive view of market dynamics and improve the predictive power of the model. This could involve exploring alternative data sources, such as alternative data sets or proprietary data sources, to supplement existing data and enrich the analysis.

2. Increase in Stock Quantity: Increasing the number of stocks included in the analysis can offer greater diversification benefits and enhance the robustness of portfolio optimization strategies. By expanding the universe of stocks considered for inclusion in the portfolio, investors can access a broader range of investment opportunities and potentially improve the Information Ratio of the optimized portfolios. This could involve broadening the scope of the analysis to include a larger set of securities from various sectors or geographic regions.

3. Expansion of Related Factors: While the study has identified several key factors influencing stock returns, there may be additional factors that have not been explored. Continuously incorporating new factors into the APT model can enhance its predictive capabilities and adaptability to changing market conditions. Researchers should explore the potential inclusion of additional factors, such as macroeconomic indicators, industry-specific variables, or sentiment data, to capture a more comprehensive set of drivers influencing asset prices. This iterative approach to factor selection can lead to greater accuracy and robustness in portfolio construction and risk management.

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6.3 Limitations and Future Work

1. Quarterly Data Limitation: Addressing the limitation of limited quarterly data is crucial for improving the precision and accuracy of the model, especially considering that the dataset comprises only 40 samples over a 10-year period. Future research efforts should focus on accessing or collecting more granular, high-frequency data to capture finer market dynamics and reduce the potential for information lag.

2. Implementation of Risk Management and Rebalancing Strategies: While ideas for risk management and rebalancing have been identified, they have not been implemented in practice. Future iterations of the study should prioritize the implementation of these strategies to evaluate their effectiveness in managing portfolio risk and optimizing performance. This could involve developing and testing various risk management techniques, such as stop-loss mechanisms, volatility targeting, or dynamic asset allocation strategies, to mitigate downside risk and enhance portfolio resilience.

3. Back Test and Forward Test Opportunity: The absence of back-testing and forward-testing represents a significant opportunity for future research. Conducting rigorous testing of the model using historical data (back-testing) and out-of-sample data (forward-testing) can validate its robustness and predictive power across different market environments. This iterative testing process can help refine the model parameters, validate its assumptions, and enhance its reliability for real-world application. Researchers should prioritize conducting comprehensive back-testing and forward-testing exercises to assess the model's performance under various scenarios and validate its suitability for practical investment decision-making.

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เอกสารนี้เป็นเอกสารที่สงวนไว้สำหรับการใช้งานเพื่อการศึกษาเท่านั้น ไม่อนุญาตให้นำไปใช้ประโยชน์ด้านการค้า ไม่ว่ากรณีใดๆ ทั้งสิ้น อีกทั้งห้ามมิให้ดัดแปลงเนื้อหาและต้องอ้างอิงถึงเจ้าของเอกสารทุกครั้งที่มีการนำไปใช้

Appendix A: Literature Review

Appendix 1.1A: Literature Review

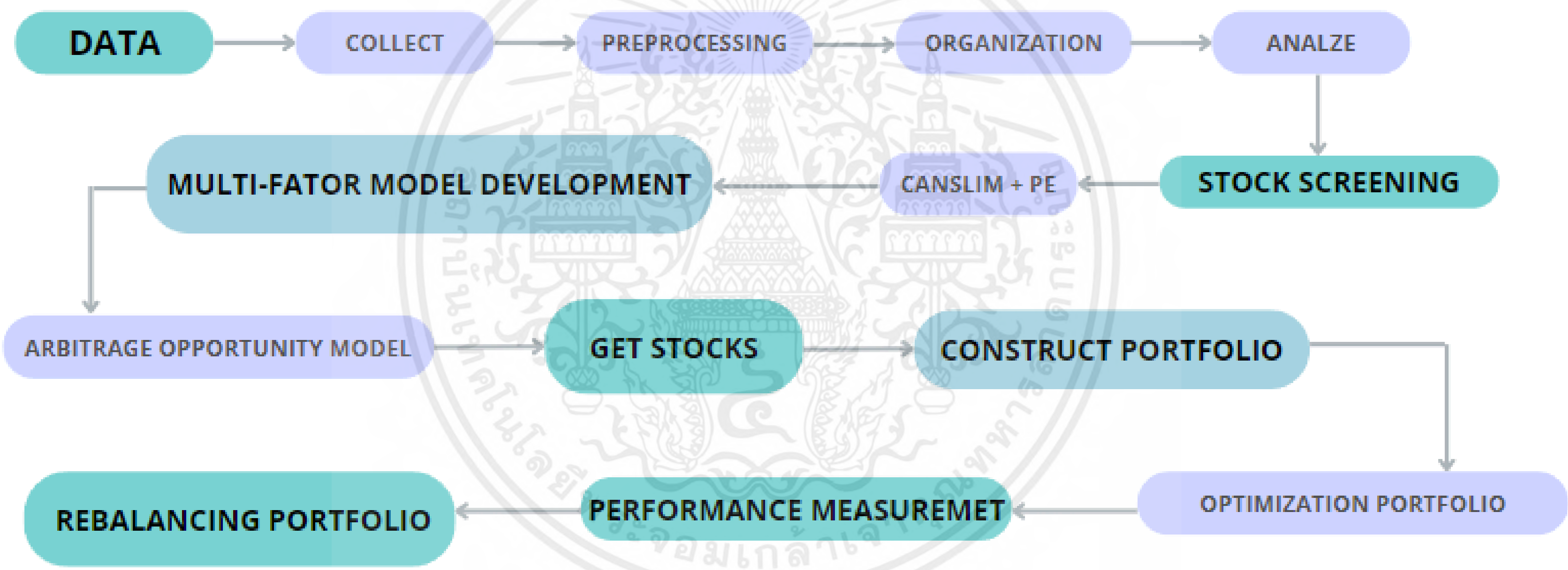
Name of reseacher	Title	Year	Interested Variable	Method	Conclusion
Thanakorn Pisudsin	Study on the model of stock price that the CANSLIM system screening on the stock exchange of Thailand	2016	CANSLIM strategy screening stock -Current quarterly earnings(EPS) -Annual earning(ROE) -New product -Supply&Demand -Leader or Laggard -Institutional Sponsorship -Market direction	-Choose stock by using CANSLIM screening stock -Construct a portfolio by using volume factor PE factor and On-balance volume to calculate the probabilities of the price of the stock success to goal. -Separate in 3 cases, 1. screen stock by CANSLIM each quarterly 2. Analyze return from portfolio construction during 9 years 3. Analyze factor that has an impact on goal price	-The CANSLIM investment strategy can be effectively applied in the Thai stock market, yielding high returns of up to 252.2% from 2009 to 2015. - The study suggests a correlation between trading volume and future securities returns, reinforcing the success potential of breakout price patterns during price compression phases.
Kanis SaengChot	Profitability, Investment and Asset Pricing: Reconciling the Valaluation and the q-Theory Approaches in the thai Stock market	2020	Fama-French 6-factor Model { Market Risk, Size (SMB), Value (HML) ,Profitability (RMW), Investment (CMA), Momentum (UMD) } Q-Factor Model {Market Risk, Size (ME), Investment (I/A), Profitibality (ROE), Expected Growth (EG) }	Construct mimick Portfolios -Fama-French (2018) 6-factor model with double-sorting (2x3 Portfolios) -Q-factor model with Triple-sorting (2x3x3 portfolios). -Factor spanning regression of individual factors, Intercept test in test assets -GRS Statistic Test: Test Good or Bad of Assets Pricing Model -Alpha Asset Test: Test Significant in each Factor	-The performance of both models performs well, but on different aspects which the strengths of the two into a better-fitting model that incorporates market risk, size, value, profitability, and investment effects.
Athiphat Rojanawutthitikhun	Factors affecting securities prices in commercial banks in the Stock Exchange of Thailand	2011	Inflation rate Actual deposit interest rates Average dividend Real GDP	Multiple Regression Analysis	-Real GDP was significantly related to the price of securities in the commercial bank group on the Stock Exchange of Thailand at the 0.05 level.
Supitcha Tirapat	The Impact of Economic Factors on Industry Group Index in the Stock Exchange of Thailand	2012	Indices of stock prices for each industry group Volume of securities purchased by foreign investors (FDI) Interest rate for 1 year baht loan (INT) Monthly average gold bar price (GOLD) Exchange rate of the baht to the US dollar (EX) Business Confidence Index (BSI) crude oil price (OIL) general inflation rate (INF)	Multiple Regression Analysis	Different effects on the movement of stock price indexes in different industry groups. - FDI same direction to the stock price indices of the energy and utilities sector, banking sector, and information and communications technology sector. - GOLD opposite direction with the group stock price index. Energy and Utilities and food and beverage stocks - EX opposite direction with the banking and commercial stock price indices. - BSI same direction as the information technology and communications stock price index and commercial stocks. - Oil same direction as the energy and utilities stock price index. - I same direction as the food and beverage stock price index.

Appendix 1.2A: Continue literature reviews form table 1

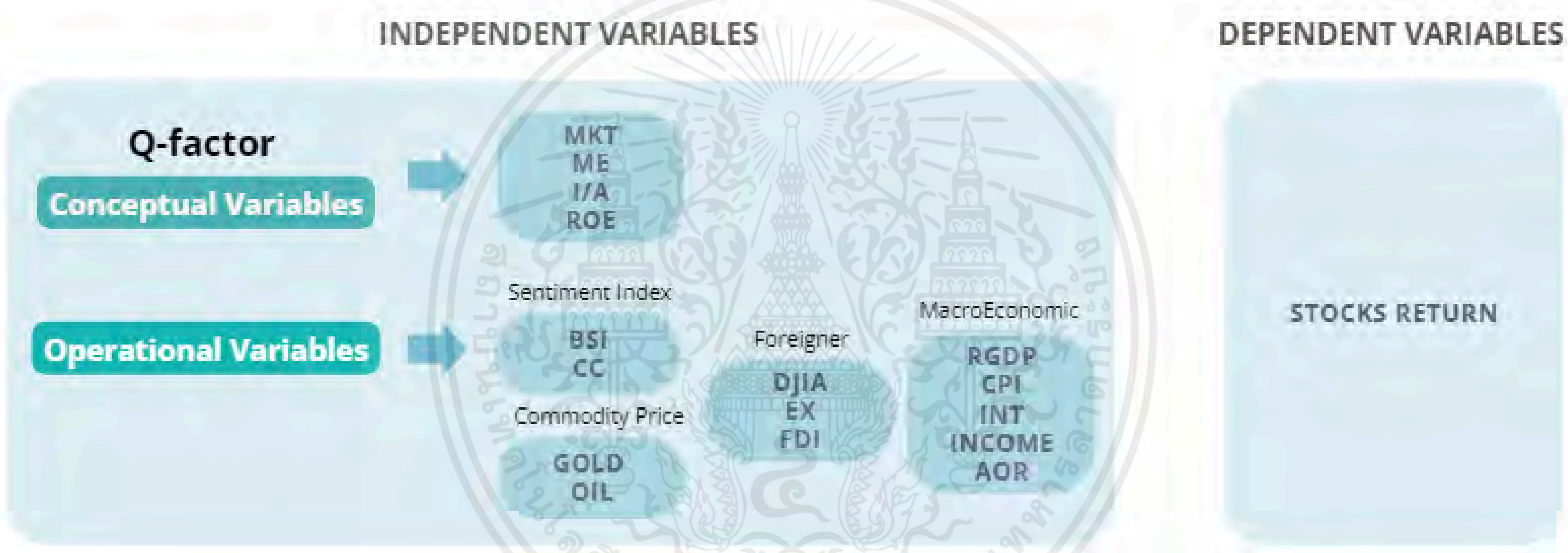
Name of reseacher	Title	Year	Interested Field	Method	Conclusion
Supitcha Tirapat	The Impact of Economic Factors on Industry Group Index in the Stock Exchange of Thailand	2012	Indices of stock prices for each industry group Volume of securities purchased by foreign investors (FDI) Interest rate for 1 year baht loan (INT) Monthly average gold bar price (GOLD) Exchange rate of the baht to the US dollar (EX) Business Confidence Index (BSI) crude oil price (OIL) general inflation rate (INF)	Multiple Regression Analysis	Different effects on the movement of stock price indexes in different industry groups. - FDI same direction to the stock price indices of the energy and utilities sector, banking sector, and information and communications technology sector. - GOLD opposite direction with the group stock price index. Energy and Utilities and food and beverage stocks - EX opposite direction with the banking and commercial stock price indices. - BSI same direction as the information technology and communications stock price index and commercial stocks. - Oil same direction as the energy and utilities stock price index. - I same direction as the food and beverage stock price index.
Rattanaporn Saelee Summarn Pankham	Factors affecting securities prices in commercial banks in the Stock Exchange of Thailand	2018	Dow Jones Industrial Index (DJIA) Exchange rate of US Dollar to Thai Baht (USD/THB) Consumer Price Index (CPI) Inflation rate (INF) Stock Price Index of the Stock Exchange of Thailand (SET Index)	Multiple Regression Analysis Stepwise Regression Importing all variables (Enter Regression)	Commercial banks - DJIA - USD/THB - SET Index - CPI - INF
Sasipa Pojanavatee	Tests of a Four-Factor Asset Pricing Model: The Stock Exchange of Thailand	2020	Market Excess Return (RM) Size (SMB) Value (HML) Liquidity (ILLIQ)	Multiple Regression Analysis	-Pay more attention to value and liquidity effects in the Consumer Products shares.
Ludan Theron & Gary van Vuuren	The maximum diversification investment strategy: A portfolio performance comparison	2018	Most Diversified (MD) portfolio and three alternatives: a Minimum Variance portfolio, an Equally-Weighted portfolio, and a Tangent (or Maximum Sharpe ratio) portfolio.	Evaluate portfolio performance using cumulative returns, the Sharpe ratio, and daily volatilities.	- Tangent (TG) portfolio outperformed others consistently while Unconstrained TG portfolio had returns exceeding 2,500% - Minimum Variance (MV) portfolio showed lowest returns and volatility - Most Diversified (MD) portfolio underperformed due to ineffective diversification
Wipha Thomyamongkol	An evaluation of risk adjusted performance ratios for Thai Mutual Funds	2020	Five popular risk adjusted performance ratios including Sharp ratio, Treynor ratio, Jensen's alpha ratio, Information ratio, and Sortino ratio.	The methodology utilizes various risk-adjusted performance ratios to compare and identify the best-performing fund.	Most ratios prove effective, except the Sortino ratio, which underperforms in the gold sector.

Appendix B: Research Methodology

Appendix 1B : Operational Roadmap



Appendix 2B : Factor Relation



Appendix 3B : Factors Declaration

Factors Definition

FACTORS	SYMBOL	NAME	UNIT	DIRECTION	FORMULA
Stock price	STOCK PRICE	Individual Stock Price	Baht	-	-
Q-factor	MARKET	Market Risk Premium	%	(+)	(Return_Market - Return_Risk-Free)
	ME	Book values	Baht	(+)	(Total Assets - Total Liabilities)
	I/A	Investment	Baht	(+)	-
	ROE	Profitability	%	(+)	-
MacroEconomic	RGDP	Real Gross Domestic Product	Baht	(+)	-
	CPI	Consumer Price Index	Points	(-)	-
	INT	Minimum Lending Rate	%	(-)	-
	INCOME	Thai Avg. Monthly wages	Baht	(+)	-
	AOR	3-Month Booking Rate	%	(+)	-
Commodity Price	GOLD	Gold Bar Price	Baht/ Avg. bar	(-)	-
	OIL	Crude Oil Price	$/Barrel	(-)	-
Sentiment Index	BSI	Business Sentiment Index	Points	(+)	-
	CC	Consumer Confident	Points	(+)	-
Foreigner	DJIA	Dow Jones Industrial Avg.	Points	(+)	-
	EX	Exchange Rate	USD/THB	(+)	-
	FDI	Foreign Direct Investment	Baht	(+)	-

Appendix 4B : CANSLIM + PE Valuation

CURRENT EARNING

CRITERIA	c
STOCK	EPS FQ YOY
TOP	72.68%
BCP	21.98%
⋮	⋮
EGCO	-10.01%

ANNUAL EARNING

CRITERIA	A
STOCK	ROE
COM7	44.81%
ADVANC	36.47%
⋮	⋮
IRPC	-8.02%

CRITERIA	A
STOCK	EPS 3Y Growth
TOP	846.87%
MBK	98.33%
⋮	⋮
ERW	-13.87%

CRITERIA	
STOCK	DE Ratio
BYD	0.025%
INTUCH	0.091
⋮	⋮
AAV	11.082

SUPPLY & DEMAND

CRITERIA	s
STOCK	Free Foat
OR	22.26%
DOHOME	22.44%
⋮	⋮
BAM	100%

CRITERIA	
STOCK	PE
BCP	3.84
RCL	3.85
⋮	⋮
ERW	-13.87%

ANNUAL EARNING

CRITERIA	A
STOCK	EPS 3Q
CKP	567.45%
BCP	22.1%
⋮	⋮
PTTGC	-67.56%

01 Calculate % change (Q2,Q1) & (Q3,Q2)

02 Sum % change

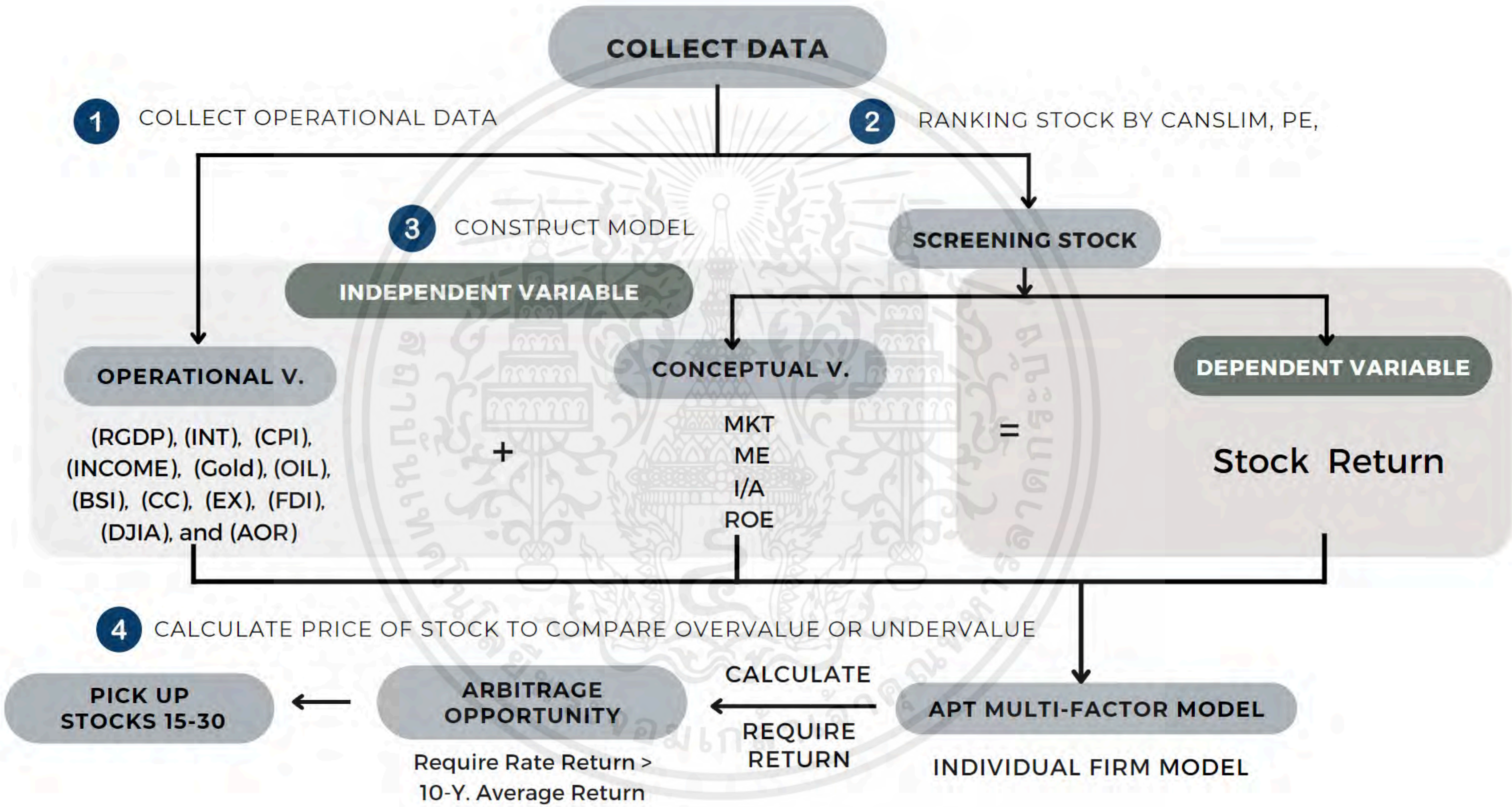
03 Give Score 1 -> 100

Total Score

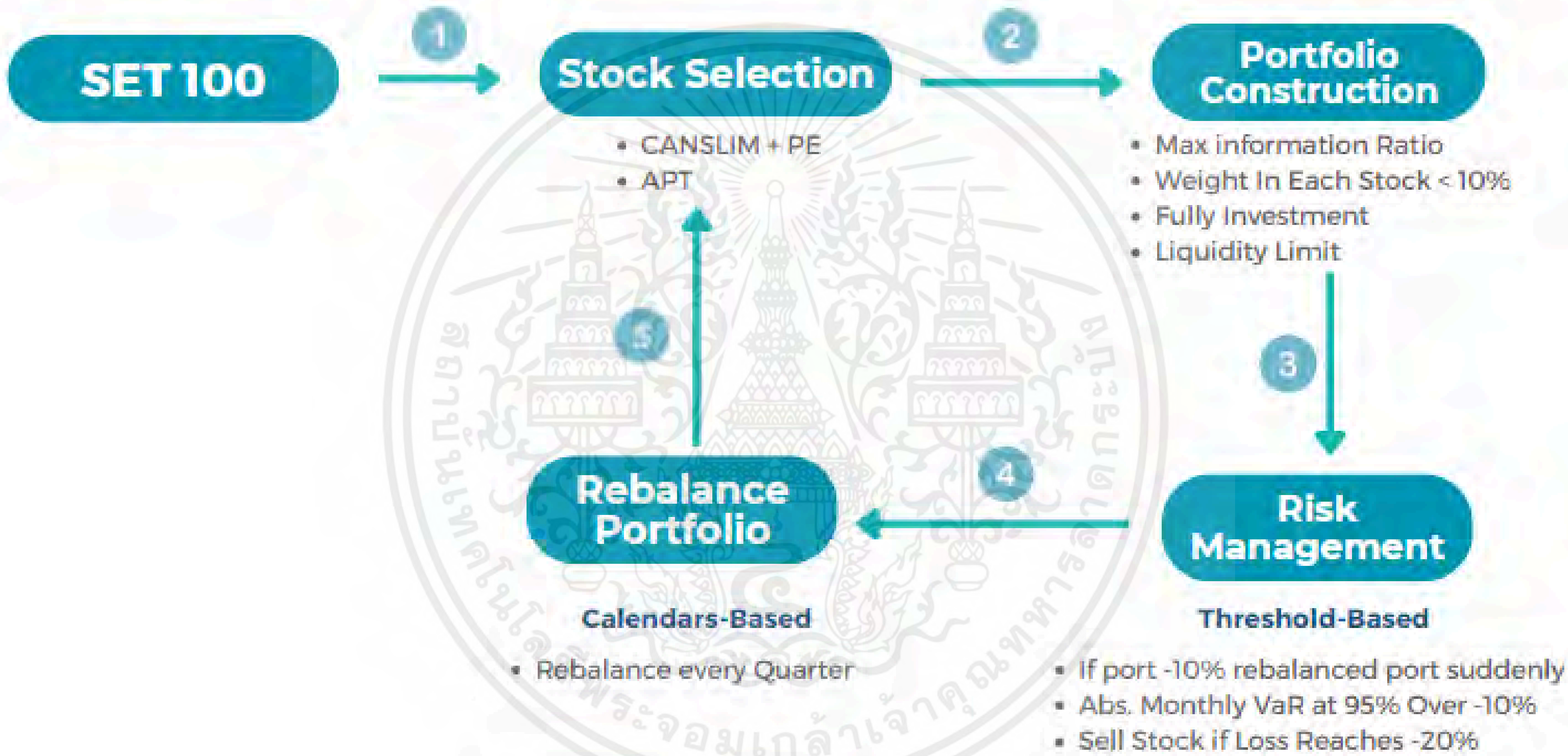
= Series(1) + Series(2) + Series(3) + Series(4) + Series(5) + 0.5xSeries(6) + Series(7)

Rank Score Lowest -> Highest Sequence 1 - 100

Appendix 5B : Model Development Phrase



Appendix 6B : Idea for Rebalancing Portfolio



Appendix C: Result and Discussion

Appendix 1.1C : Database in Excel File

Start Date	1/6/2013
End Date	30/9/2023

Number	1	2	3	4	5	6	7	8
Name	PTT PCL	Delta Elec	Airports of	Advanced	PTT Explor	Gulf Energ	CP ALL PCI	Bangkok D
Ticker	PTT TB Equity	DELTA TB	AOT TB Eq	ADVANC T	PTTEP TB I	GULF TB E	CPALL TB I	BDMS TB E
Dates	TOT_RETURN_II	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU
30/6/2013	33.5	4	16.85	288	158.5	#N/A N/A	39.846	15.75
30/9/2013	32.077	4.925	18.85	266.508	166.595	#N/A N/A	36.014	12.6
31/12/2013	29.032	5.35	16.26	208.504	169.651	#N/A N/A	42.911	11.75
31/3/2014	31.172	6.194	19.901	242.29	163.15	#N/A N/A	44.443	13.504
30/6/2014	33.153	6.561	20.363	235.858	174.061	#N/A N/A	50.092	16.956
30/9/2014	38.171	6.509	24.518	248.123	169.318	#N/A N/A	46.7	18.784
31/12/2014	34.354	7.401	29.288	276.795	118.523	#N/A N/A	44.352	17.464
31/3/2015	34.752	8.248	29.08	267.929	116.846	#N/A N/A	42.787	20.227
30/6/2015	38.625	9.92	31.631	271.32	116.846	#N/A N/A	49.19	20.227
30/9/2015	26.427	9.646	29.335	262.621	75.884	#N/A N/A	50.786	18.995
30/12/2022	49.337	109.651	84.754	303.744	259.222	57.763	80.685	34.01
31/3/2023	47.779	151.531	80.234	336.956	227.901	55.795	73.297	34.967
30/6/2023	50.813	122.074	81.364	340.135	227.144	49.448	74.747	32.893
29/9/2023	50.813	109.8	78.822	368.916	265.758	48.126	72.355	32.119

Number	90	91	92	93	94	95	96	97	98	99
Name	Sri Trang C	TQM Alph	Regional C	Srinanapo	Ratchthan	Absolute C	PTG Energ	Sino-Thai I	Precious S	Sabuy Tec
Ticker	STGT TB E	TQM TB Ec	RCL TB Eq	SNNP TB E	PTG TB Eq	THANI TB	ACE TB Eq	PSL TB Eq	STEC TB E	SABUY TB
Dates	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU
30/6/2013	#N/A N/A	#N/A N/A	5.85	#N/A N/A	4.06	1.862	#N/A N/A	13.599	19.5	#N/A N/A
30/9/2013	#N/A N/A	#N/A N/A	6.35	#N/A N/A	3.9	1.585	#N/A N/A	14.38	22.7	#N/A N/A
31/12/2013	#N/A N/A	#N/A N/A	6.3	#N/A N/A	3.783	1.49	#N/A N/A	16.552	13.2	#N/A N/A
31/3/2014	#N/A N/A	#N/A N/A	6.45	#N/A N/A	3.716	1.617	#N/A N/A	22.049	16.594	#N/A N/A
30/6/2014	#N/A N/A	#N/A N/A	6.7	#N/A N/A	3.633	1.641	#N/A N/A	19.121	23.499	#N/A N/A
30/9/2014	#N/A N/A	#N/A N/A	10.6	#N/A N/A	5.418	1.529	#N/A N/A	18.882	27.828	#N/A N/A
31/12/2014	#N/A N/A	#N/A N/A	8.45	#N/A N/A	6.089	1.337	#N/A N/A	10.7	24.015	#N/A N/A
31/3/2015	#N/A N/A	#N/A N/A	9.1	#N/A N/A	10.467	1.612	#N/A N/A	11.251	22.31	#N/A N/A
30/6/2015	#N/A N/A	#N/A N/A	9.805	#N/A N/A	16.095	1.352	#N/A N/A	9.268	24.405	#N/A N/A
30/9/2015	#N/A N/A	#N/A N/A	7.076	#N/A N/A	15.463	1.197	#N/A N/A	7.312	25.348	#N/A N/A
30/12/2022	12.584	43.21	41.468	20.665	17.447	5.532	2.753	19.98	15.928	11.409
31/3/2023	12.836	37.108	39.6	25.188	17.086	5.086	2.325	17.002	15.097	12.216
30/6/2023	9.61	30.08	35.416	24.819	14.889	4.474	1.988	11.818	10.544	9.158
29/9/2023	8.578	38.287	32.957	21.838	11.411	4.224	1.631	12.397	11.263	7.06

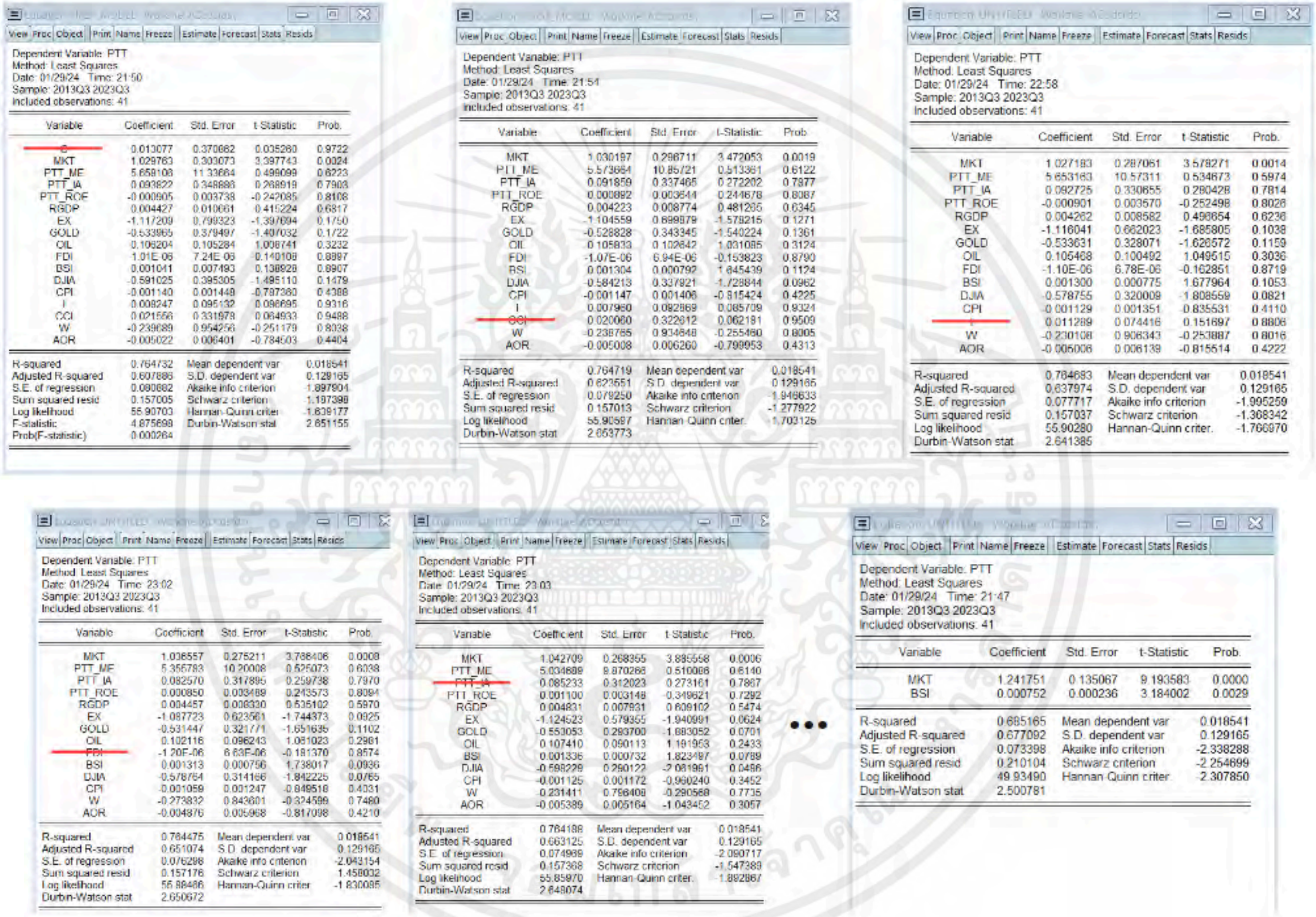
\+ ≡ Total_Return_Index ▾ Price ▾ MarketCap ▾ ROE ▾ PE ▾ TradeVolume ▾ PPE ▾ Inventories ▾

Appendix 1.2C : Database in Excel File

Start Date	1/6/2013										
End Date	30/9/2023										
Name	Consumer Price	Real GDP	Consumer	Gold Bar P	Crude Oil F	Business S	Foreign Di	Dow Jone	Interest Ra	Exchange I	Thai Wage
Ticker	THCPIMOM Inc	THG PQQ I	THCCI Ind	THGOBRSI	USCRWTIC	THBSI Inde	THFDITTL	INDU Inde	BTRRHALL	USDTHB C	THWGTL Ir
Dates	TOT_RETURN_	TOT_RETU	TOT_RETU	PX_LAST	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	TOT_RETU	PX_LAST	TOT_RETU
30/6/2013	0.15	-0.6	81.6	18250	96.56	49.9	-98.65	15003.46	2.5	31.035	11880.3
30/9/2013	0.17	0.70	77.9	19850	102.33	47.5	6098.27	15320.99	2.5	31.283	12255.22
31/12/2013	0.14	-0.10	73.4	18850	98.42	45	6590.41	16886.37	2.25	32.865	12163.15
31/3/2014	0.2	-0.40	68.8	19900	101.58	49.4	-397.51	16860.93	2	32.43	12772.48
30/6/2014	-0.11	0.60	75.1	20200	105.37	48	1516.23	17338.19	2	32.454	13237.76
30/9/2014	-0.17	0.90	79.2	18650	91.16	48.9	1912.1	17663	2	32.42	13386.23
31/12/2014	-0.51	1.10	81.1	18550	53.27	49	1944.64	18582.07	2	32.904	13581.1
31/3/2015	0.17	0.50	77.7	18200	47.6	52.4	1649.71	18642.61	1.75	32.533	13247.89
30/6/2015	0.1	0.40	74.4	18800	59.47	49.1	3417.13	18587.87	1.5	33.769	13324.95
30/9/2015	-0.05	1.50	72.1	19350	45.09	47.3	763.34	17290.5	1.5	36.31	13599.05
31/12/2015	-0.39	0.60	76.1	18300	37.04	49.9	3097.41	18621.49	1.5	36.083	13774.29
31/3/2016	0.22	0.80	73.5	20550	38.34	51.5	3513.81	19031.01	1.5	35.185	13496.4
30/6/2016	0.03	0.90	71.6	21950	48.33	50.4	1347.83	19424.73	1.5	35.138	13652.19
30/9/2016	0.04	0.90	74.2	21800	48.24	50.3	-3426.91	19958.96	1.5	34.673	13803.15
30/9/2022	0.22	1.00	44.6	29800	79.49	49.6	2079.86	35802.5	1	37.73	15212.83
31/12/2022	-0.06	-1.10	49.7	29850	80.26	48.4	2221.19	41534.31	1.25	34.605	15416.29
31/3/2023	-0.27	1.70	53.8	31950	75.67	52.9	2795.36	41920.34	1.75	34.198	15117.83
30/6/2023	0.6	0.20	56.7	32000	70.64	51	279.8	43584.04	2	35.455	15411.82
30/9/2023	-0.36	0.80	58.7	32150	90.79	50.4	279.8	42669.4	2.5	36.412	15452.59

All Factors

Appendix 2C : Stepwise elimination Approach (Example)



PTT Model $R_{ptt} = 0.02652996 + 1.24175(MKT) + 0.000752(BSI)$

Appendix 3C : Model Troubleshooting and Verification (Example)

Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	1.256109	Prob. F(2,37)	0.2966
Obs*R-squared	2.606813	Prob. Chi-Square(2)	0.2716

Heteroscedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.437020	Prob. F(2,38)	0.6492
Obs*R-squared	0.921839	Prob. Chi-Square(2)	0.6307
Scaled explained SS	1.747535	Prob. Chi-Square(2)	0.4174

Multicollinearity Test

Variance Inflation Factors
Date: 03/25/24 Time: 11:41
Sample: 2013Q3 2023Q3
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF
MKT	0.092454	4.567310
ME	123.9659	3.351065
IA	0.111524	1.773339
ROE	1.25E-05	10.08429
RGDP	7.40E-05	2.139049
EX	0.443099	4.476217
GOLD	0.117047	2.353208
OIL	0.009874	4.047704
FDI	3.61E-11	2.303867
BSI	6.67E-07	10.69806
DJIA	0.129561	5.703076
CPI	1.83E-06	2.595447
I	0.008585	2.431732
CCI	0.105321	3.108149
W	0.925489	2.053793
AOR(-1)	4.01E-05	1.810886

Appendix 4C : Result of Portfolio Construction in Python

	Symbol	Proportion	Std	Return
0	VGI	0.0000	0.5458	-0.0485
1	TOP	0.0000	0.6671	0.2882
2	BCP	0.0648	0.5537	0.3481
3	ACE	0.0000	0.7975	-0.4611
4	BH	0.1000	0.4619	0.5306
5	OSP	0.0706	0.3858	0.1975
6	OR	0.0000	0.1691	-0.5676
7	HANA	0.0945	0.7527	0.7454
8	TQM	0.0366	1.0040	1.1552
9	AOT	0.1000	0.3971	0.5376
10	BDMS	0.1000	0.3706	0.2779

	Symbol	Proportion	Std	Return
11	SPRC	0.0711	0.7475	0.4516
12	STGT	0.0000	0.5132	-1.2704
13	SCGP	0.0000	0.5568	0.0876
14	AP	0.1000	0.6765	0.5845
15	MTC	0.0000	0.7385	0.6576
16	THG	0.0162	1.0453	0.8150
17	BEM	0.1000	0.3667	0.2728
18	SAWAD	0.0513	0.7701	0.7091
19	TCAP	0.0949	0.3895	0.3538
20	AWC	0.0000	0.6532	-0.0860
21	TIDLOR	0.0000	0.4077	-0.5463

Appendix D: Source Code

Link: [CANSLIM to APT Finalized Project.ipynb - Colaboratory]

Appendix 1D: CANSLIM

```
C = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'EPS FQ YOY')
A = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'EPS Growth 3yrs')
N = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'ROE')
S = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'DE Ratio')
L = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'Free Float')
I = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'PE')
M = pd.read_excel('/content/drive/MyDrive/KWIDB/CANSLIM(1).xlsx', 'EPS 3Q')
```

```
new_C = C.T
new_C.drop(new_C.index[0] , inplace=True)
new_C.columns = ['C']
display(new_C)
new_C['rank C'] = new_C['C'].rank(method='min',na_option='bottom',ascending=False)
display(new_C)
#========================================
new_A = A.T
new_A.drop(new_A.index[0] , inplace=True)
new_A.columns = ['A']
display(new_A)
new_A['rank A'] = new_A['A'].rank(method='min',na_option='bottom',ascending=False)
display(new_A)
#========================================
new_N = N.T
new_N.drop(new_N.index[0] , inplace=True)
new_N.columns = ['N']
display(new_N)
new_N['rank N'] = new_N['N'].rank(method='min',na_option='bottom',ascending=False)
display(new_N)
#========================================
new_S = S.T
new_S.drop(new_S.index[0] , inplace=True)
new_S.columns = ['S']
display(new_S)
new_S['rank S'] = new_S['S'].rank(method='min',na_option='bottom',ascending=True)
display(new_S)
#========================================
new_L = L.T
new_L.drop(new_L.index[0] , inplace=True)
new_L.columns = ['L']
display(new_L)
new_L['rank L'] = new_L['L'].rank(method='min',na_option='bottom',ascending=True)
display(new_L)
#========================================
new_M = M.T
new_M.drop(new_M.index[0] , inplace=True)
new_M.columns = ['M1','M2','M3']
new_M['%_Change_M1M2'] = (new_M['M2'] - new_M['M1'])/np.abs(new_M['M1'])
new_M['%_Change_M2M3'] = (new_M['M3'] - new_M['M2'])/np.abs(new_M['M2'])
new_M['Total_%Change'] = new_M['%_Change_M2M3'] + new_M['%_Change_M1M2']
new_M['rank M'] = new_M['Total_%Change'].rank(method='min',na_option='bottom',ascending=False)
display(new_M)
#========================================
```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```
stock_pe = pd.read_excel('/content/drive/MyDrive/KWIDB/Proj_Valuation_Part2.xlsx','PE')
sector = pd.read_excel('/content/drive/MyDrive/KWIDB/Proj_Valuation_Part2.xlsx','Sector')
industry_pe = pd.read_excel('/content/drive/MyDrive/KWIDB/Proj_Valuation_Part2.xlsx','PE_Indus')

#Change Header
stock_pe.columns = stock_pe.iloc[2]

stock_pe = stock_pe.rename(columns={np.nan: 'Dates'})
header = list(stock_pe.columns)
header_real = []
for i in range (len(header)):
 header_real.append(header[i].split()[0])
#print(header_real)

stock_pe.columns = header_real
stock_pe.columns.name = "PE"

#Drop Row
stock_pe.drop(stock_pe.index[0:6], inplace = True)

#Change Date to be index
stock_pe.set_index('Dates', inplace = True)
#===================================================================
#Change Header
industry_pe.columns = industry_pe.iloc[2]

industry_pe = industry_pe.rename(columns={np.nan: 'Dates'})
header = list(industry_pe.columns)
header_real = []
''' for i in range (len(header)):
 header_real.append(header[i].split()[0]) '''
#print(header_real)

industry_pe.columns = header
industry_pe.columns.name = "Industry PE"

#Drop Row
industry_pe.drop(industry_pe.index[0:6], inplace = True)

#Change Date to be index
industry_pe.set_index('Dates', inplace = True)
#===================================================================
```


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```python
new_I = I.T
new_I.drop(new_I.index[0] , inplace=True)
new_I.columns = ['I']
#Add Sector Column
new_I['Sector PE'] = ''
#Add Ratio Column
new_I['Ratio'] = ''
display(I)

#Loop
for i in (stock_pe.columns):
  #store stock's PE
  recently_pe = stock_pe[i].iloc[-1]

  #Find sector
  lookup = i+' TB Equity'
  stock_sector = sector.loc[sector['Ticker']==lookup]['Unnamed: 1']

  #store sector's PE

  indus_pe = industry_pe[stock_sector].iloc[-1]

  new_I.loc[i, ['Sector PE']] = float(indus_pe)

  new_I.loc[i, ['I']] = float(recently_pe)

  new_I.loc[i, ['Ratio']] = float(recently_pe)/float(indus_pe)
  #display(new_I.loc[i, ['Ratio']])


new_I.drop(new_I.index[-1] , inplace=True)
new_I['Ratio'] = pd.to_numeric(new_I['Ratio'])
new_I['rank I'] = new_I['Ratio'].rank(method='min', na_option='bottom', ascending=True)

print(new_I.dtypes)
display(new_I)
```

```python
#==========================================
All_Stocks = pd.DataFrame()
All_Stocks['rank C'] = new_C['rank C']
All_Stocks['rank A'] = new_A['rank A']
All_Stocks['rank N'] = new_N['rank N']
All_Stocks['rank S'] = new_S['rank S']
All_Stocks['rank L'] = new_L['rank L']
All_Stocks['rank I'] = new_I['rank I']
All_Stocks['rank M'] = new_M['rank M']
All_Stocks['Total Rank'] = (All_Stocks['rank C'] + All_Stocks['rank A'] + All_Stocks['rank N'] + All_Stocks['rank S']
                            + All_Stocks['rank L'] + All_Stocks['rank M']) + (All_Stocks['rank I'] * 0.5)/6.5
All_Stocks['Rank'] = All_Stocks['Total Rank'].rank(method='min',na_option='bottom',ascending=True)

#display(All_Stocks.head(30))
top50 = All_Stocks.sort_values(by=['Rank']).head(50)
display(top50)
chosen_stock = list(top50.index.values)
print(chosen_stock)
```


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Appendix 2D: Multifactor Development

```
#df = pd.read_csv('/content/drive/MyDrive/KWIDB/PTT_Sample - Sheet1 (1).csv')
IA = pd.read_excel('/content/drive/MyDrive/KWIDB/NewData.xlsx','IA')
RP = pd.read_excel('/content/drive/MyDrive/KWIDB/NewData.xlsx','Rp')
ME = pd.read_excel('/content/drive/MyDrive/KWIDB/NewData.xlsx','ME')
ROE = pd.read_excel('/content/drive/MyDrive/KWIDB/NewData.xlsx','ROE')
Factors = pd.read_excel('/content/drive/MyDrive/KWIDB/NewData.xlsx','ALL_Factor')
```

```
header = list(ROE.columns)
header_real_roe = []
for i in range (len(header)):
  header_real_roe.append(header[i].split()[0] + " ROE")

ROE.columns = header_real_roe

ROE.set_index("Dates ROE", inplace = True)

ROE.columns.name = "Symbols"

display(ROE)

ROE.reset_index(drop=True, inplace= True)
display(ROE)
```

```
#df['Dates']=pd.to_datetime(df['Dates'])
#df=df.set_index('Dates')

header = list(IA.columns)
header_real_IA = []
for i in range (len(header)):
  header_real_IA.append(header[i].split()[0] + " IA")

IA.columns = header_real_IA

IA.set_index("Dates IA", inplace = True)

IA.columns.name = "Symbols"

display(IA)

IA.reset_index(drop=True, inplace= True)
```


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```python
header = list(RP.columns)
header_real_RP = []
for i in range (len(header)):
    header_real_RP.append(header[i].split()[0] + " RP")

RP.columns = header_real_RP
display(RP)

RP.set_index("Date RP", inplace = True)

RP.columns.name = "Symbols"

display(RP)

RP.reset_index(drop=True, inplace= True)
```

```python
header = list(ME.columns)
header_real_ME = []
for i in range (len(header)):
    header_real_ME.append(header[i].split()[0] + " ME")

ME.columns = header_real_ME

ME.set_index("Dates ME", inplace = True)

ME.columns.name = "Symbols"

display(ME)

ME.reset_index(drop=True, inplace= True)
```


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```python
def OLS(stock):
    X = Factors[['MKT', 'RGDP', 'EX', 'Gold', 'Oil', 'FDI', 'BSI', 'DJIA', 'CPI', 'I', 'CCI', 'W', 'AOR']]
    X.head()
    X['ROE'] = ROE[stock+' ROE']
    X['ME'] = ME[stock+' ME']
    X['IA'] = IA[stock+' IA']

    #Put Lag -1
    #X['MKT'] = X['MKT'].shift(1)
    #X['RGDP'] = X['RGDP'].shift(1)
    #X['Oil'] = X['Oil'].shift(1)
    #X['BSI'] = X['BSI'].shift(1)
    #X['DJIA'] = X['DJIA'].shift(1)

    #X['ME'] = X['ME'].shift(1)
    #X['ROE'] = X['ROE'].shift(1)

    #Put Lag -2
    X['AOR'] = X['AOR'].shift(1)
    #X['I'] = X['I'].shift(2)

    X = X.dropna()
    #display(X)

    Y = RP[stock+' RP']
    #Y.drop([0,1], inplace=True)
    Y = Y.dropna()
    #display(Y)

    if len(X) != len(Y):
      #print(len(X),len(Y))
      if len(Y) > len(X):
        c = len(Y) - len(X)
        Y.reset_index(drop=True, inplace= True)
        X.reset_index(drop=True, inplace= True)
        Y.drop(Y.index[0:c], inplace=True)
        Y.reset_index(drop=True, inplace= True)

      else:
        c = len(X) - len(Y)
        Y.reset_index(drop=True, inplace= True)
        X.reset_index(drop=True, inplace= True)
        X.drop(X.index[0:c], inplace=True)
        X.reset_index(drop=True, inplace= True)
```


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```
Y.reset_index(drop=True, inplace= True)
X.reset_index(drop=True, inplace= True)
display(X)
display(Y)
print(len(X),len(Y))
X = sm.add_constant(X)

while True:

    #break loop if none features
    #if len(X.columns) == 0:
      #break

    # Fit the model
    model = sm.OLS(Y, X).fit()
    display(X)

    # Get the summary of the model
    summary = model.summary()
    print(summary)

    # Extract the p-values of the coefficients
    p_values = sorted(list(model.pvalues))[-1]

    #print(summary.tables[1].data)

    # Identify the predictors with p-values exceeding the threshold
    lend = sorted(list(model.pvalues))

    max = 0.05
    for i in range (1,len(lend)+1):
      if float(summary.tables[1].data[i][4]) > float(max):
        max = summary.tables[1].data[i][4]
        #print(summary.tables[1].data[i][0])
      #print(max,summary.tables[1].data[i][0])

    for i in range (1,len(lend)+1):
      predictors_to_remove = 0
      if float(max) == float(summary.tables[1].data[i][4]):
        predictors_to_remove = summary.tables[1].data[i][0]
        #print(max,summary.tables[1].data[i][4])
        break
```

```
    # Break the loop if no predictors exceed the threshold
    if (predictors_to_remove) == 0:
      break

    # Remove the corresponding columns from your matrix of independent variables
    X = X.drop(columns=predictors_to_remove)

  # The final model is stored in the variable 'model'

    print(model.summary())
```

```
#========================================== Auto Correlation =============================================
#perform Breusch-Godfrey test at order p = 1
if ((summary.tables[1].data[1][4].split()[0])== 'nan'):
      pass
else:
  au = dg.acorr_breusch_godfrey(model, nlags=1)
  if au[1] > 0.05:
    print("This Model don't have Autocorrelation, while P-Value @",au[1])
  else:
    print("This Model have Autocorrelation, while P-Value @",au[1])
    auto_correlation[stock] = au[1]
#P อ่านตัวที่ 2
#=========================================================================================================
```


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```python
#========================================= Heteroscedasticity ============================================
''' #perform White's test
white_test = het_white(model.resid,  model.model.exog)

#define labels to use for output of White's test
labels = ['Test Statistic', 'Test Statistic p-value', 'F-Statistic', 'F-Test p-value']

#print results of White's test
print(dict(zip(labels, white_test))) '''

#Check if have constant
if ((summary.tables[1].data[1][4].split()[0])== 'nan'):
        pass
else:
  con = 'const'
  check = 'no'
  for i in (list(summary.tables[1].data)):
    if con in i:
      check = 'yes'

  if check == 'no':
    X = sm.add_constant(X)

  BPResults = het_breuschpagan(model.resid, X)
  alpha = 0.05
  if  BPResults[1] > alpha:
      print('Residual errors are homoscedasticity')
  else:
      print('Residual errors are heteroscedastisticity')
      hetero[stock] = BPResults[1]
#==========================================================================================================
```

```python
#========================================= Multicolinearity ============================================
if ((summary.tables[1].data[1][4].split()[0])== 'nan'):
      print((summary.tables[1].data[1][4].split()[0]))
      pass
else:
  vif = pd.DataFrame()
  vif['Features'] = X.columns
  vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
  vif['VIF'] = round(vif['VIF'], 2)
  vif = vif.sort_values(by = "VIF", ascending = False)
  print(vif)
#==========================================================================================================
```

```python
try:
  sig[stock] = {}
  for j in range (len(summary.tables[1].data)-1):
    if ((summary.tables[1].data[j+1][4].split()[0])== 'nan'):
      (summary.tables[1].data[j+1][4])
      break
    sig[stock][summary.tables[1].data[j+1][0]] = float(summary.tables[1].data[j+1][1].split()[0])
  print(sig)
except ValueError:  #raised if `y` is empty.
  pass
```

```python
#Get list of stocks
header = list(ROE.columns)
header_real = []
for i in range (len(header)):
  header_real.append(header[i].split()[0])
print(header_real)
```

```python
#OLS('CPF')
for i in header_real:
  OLS(i)
```


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Appendix 3D: Arbitrage Pricing Theory (APT) Model

```
require = {}
rf = 0.0211

for i in sig:
  a = 0
  for j in sig[i]:
    #print(list(sig.keys())[i])
    if j == 'ROE':
      a += float(sig[i][j]) * ROE[i+' ROE'].mean()
      #print(a)

    elif j == 'ME':
      a += float(sig[i][j]) * ME[i+' ME'].mean()
      #print(a)

    elif j == 'IA':
      a += float(sig[i][j]) * IA[i+' IA'].mean()
      #print(a)

    elif j == 'const':
      a += float(sig[i][j])

    else:
      a += float(sig[i][j]) * (float(Factors.mean()[j])-rf)
      #print(a)

  require[i] = a+rf
  #print(i,'\t',require[i])
req = pd.DataFrame.from_dict(require,orient='index')
req.columns =['require return']
print(sig)
display(req)
```


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```
print(list(RP))
print(req)
req['RP'] = list(RP.mean())
display(req)
print(len(req.loc[(req['require return']>req['RP'])]))
display((req.loc[(req['require return']>req['RP'])]))
display(top50)
result = pd.concat([top50, req], axis=1, join="inner")
display(result)
final_result = result.loc[(result['require return']>result['RP']) & (result['RP']>0)]
display(final_result)
```

```
rf = 0.0211
index = ['^SET']
#stocks = ['IVL','PTTEP','AP','RCL','GPSC','EA','KTC','GULF','SINGER','JMT']
stocks = list(final_result.index.values)
year_start = '2013'
year_end = '2023'
```

Appendix 4D: Portfolio Construction

```
#Set 100 Index Return
ind = pd.read_excel('/content/drive/MyDrive/KWIDB/Quarter_Project.xlsx', 'Market Premium Calculation')
ind.drop(ind.index[0] , inplace=True)
ind.drop(ind.index[0] , inplace=True)

set_ret = pd.DataFrame()
set_ret['SET RP'] = ind['%Change']
set_ret.reset_index(drop=True, inplace= True)
display(set_ret)

for i in stocks:
    set_ret = pd.concat([set_ret,RP[i+' RP']], axis=1)

#set_ret = pd.concat([set_ret, RP],axis=1)
display(set_ret)
```


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ไม่ว่ากรณีใดๆ ทั้งสิ้น อีกทั้งห้ามมิให้ดัดแปลงเนื้อหาและต้องอ้างอิงถึงเจ้าของเอกสารทุกครั้งที่มีการนำไปใช้

```python
Excess_Return = pd.DataFrame()
for i in list(set_ret.columns):
    Excess_Return[i] = set_ret[i] - set_ret.mean()[i]

display(Excess_Return)

print("Mean (Monthly):",set_ret.mean())
print("Mean (Yearly):",set_ret.mean()*4)
print("Standard Deviation (Monthly):",set_ret.std())
print("Standard Deviation (Yearly) :",set_ret.std()*np.sqrt(4))
print("Sharpe Ratio:",((set_ret.mean()*4)-(rf))  /  (set_ret.std()*np.sqrt(4)))


Excess_Return = Excess_Return.drop(columns='SET RP')
display(Excess_Return)
```

```python
Ret = list(set_ret.mean()*4)
del Ret[0]
Excess_Yearly = Ret

SD_X = list(set_ret.std()*np.sqrt(4))
del SD_X[0]
print(set_ret.mean()*4)
```

```python
SD = list(set_ret.std()*np.sqrt(4))
cov_matrix = Excess_Return.cov()
print(SD)
del SD[0]

SD = pd.DataFrame(SD, index=cov_matrix.columns).T

print(SD, '\n', cov_matrix)

SD_cov = SD.dot(cov_matrix)

print(SD_cov)
print(set_ret)
```

```python
limit_weights = []
port_size = 1000000000
print(stocks)
for i in stocks:
  stock = yf.download(tickers = i+".BK", start=year_start+'-01-01', end=year_end+'-09-30', interval = "1d")
  if len(stock) == 0: #If can't download data from yahoo finance, put limit weights by using average from portfolio size
    limit_weights.append(round(1/(len(stocks)),4))
  else:
    price = ((stock['Volume'][-1])/3 * stock['Close'][-1]) + ((stock['Volume'][-2])/3 * stock['Close'][-2]) + ((stock['Volume'][-3])/3 * stock['Close'][-3])
    limit_weights.append(round((price/port_size),4))

  print('\n',limit_weights)
```


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```python
def mean_variance_optimization(returns_df, cov_matrix, sd):
    # Calculate mean returns and covariance matrix
    mean_returns = returns_df
    cov_matrix = cov_matrix
    standard_deviation = sd

    SD = pd.DataFrame(standard_deviation, index=cov_matrix.columns).T
    SD_cov = (SD.dot(cov_matrix))
    SD_cov = list(SD_cov.values)

    num_assets = len(list(returns_df))

    # Function to minimize - negative portfolio returns (to maximize returns)
    def negative_portfolio_returns(weights):

        #Return on SET index average return
        benchmark = pd.DataFrame()
        benchmark['SET RP'] = set_ret.loc[:, 'SET RP']
        stock_ret = set_ret.loc[:, set_ret.columns != 'SET RP']

        #Multiply Stock Return with weights in each period
        stockWeights = stock_ret.multiply(weights)

        #Sum Portfolio Return
        port_ret = pd.DataFrame()
        port_ret['Portfolio RP'] = np.sum(stockWeights.T)

        #total chart
        tot_chart = pd.DataFrame()
        tot_chart['Port RP (%)'] =  port_ret['Portfolio RP'] *100
        tot_chart['SET RM (%)'] = benchmark['SET RP'] *100
        tot_chart['Excess Return (%)'] = tot_chart['Port RP (%)'] - tot_chart['SET RM (%)']

        tracking_error = (tot_chart['Excess Return (%)']/100).std()  # using ddof=1 for sample standard deviation
        information_ratio = (np.mean(tot_chart['Excess Return (%)']/100) *2) / (tracking_error)
        print(information_ratio)

        #print('Benchmark:',benchmark,'\nExcess Return:', excess_returns,'\nTracking Error', tracking_error,'\nInformation Ratio', information_ratio)

        return -information_ratio
```

```python
    weight_sum_constraint = [{'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1},  # sum of weights equals 1
                             #{'type': 'ineq', 'fun': lambda weights: weights - 0.001},      # each stock >= 1%
                             {'type': 'ineq', 'fun': lambda weights: 0.10 - weights}         # each stock <= 10%
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[0] - weights[0]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[1] - weights[1]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[2] - weights[2]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[3] - weights[3]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[4] - weights[4]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[5] - weights[5]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[6] - weights[6]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[7] - weights[7]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[8] - weights[8]},
                             #{'type': 'ineq', 'fun': lambda weights: limit_weights[9] - weights[9]}
    ]

    for loop in range (len(limit_weights)):
      weight_sum_constraint.append({'type': 'ineq', 'fun': lambda weights, loop=loop: limit_weights[loop] - weights[loop]})

    weight_sum_constraint = tuple(weight_sum_constraint)

    bounds = tuple((0, 1) for _ in range(num_assets))

    initial_weights = np.ones(num_assets) / num_assets

    # Perform MVO optimization
    result = minimize(negative_portfolio_returns, initial_weights, method='SLSQP', bounds=bounds, constraints=weight_sum_constraint)
    print(result)
    return result.x

def main():
    global optimized_weights
    optimized_weights = mean_variance_optimization(Excess_Yearly, cov_matrix, SD_X)
    print("Standard Deviation:", set_ret.std()*np.sqrt(4))
    print("Return:", set_ret.mean()*4)
    print("Optimal Weights:", optimized_weights)

if __name__ == "__main__":
    main()
```


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```python
mean_ret = set_ret.mean()
display(mean_ret)

#print(("Sharpe Ratio:",((set_ret.mean()*4)-rf)/(set_ret.std()*np.sqrt(4))))
Sharpe = pd.DataFrame()
Sharpe['Return RP'] = mean_ret*4
Sharpe['Standard Deviation'] = set_ret.std()*np.sqrt(4)
Sharpe['==============='] = ''
Sharpe['Sharpe Ratio'] = ((set_ret.mean()*4)-rf)/(set_ret.std()*np.sqrt(4))

Sharpe.drop(Sharpe.index[0] , inplace=True)
Sharpe['Porportion'] = optimized_weights
display(Sharpe)
```

```python
fr = pd.DataFrame()
fr['Symbol'] = list(final_result.index.values)
fr['Proportion'] = optimized_weights

std = list(set_ret.std()*np.sqrt(4))
display(std)
del std[0]

fr['Std'] = list(std)
display(fr)

R = list(set_ret.mean()*4)
del R[0]
fr['Return'] = list(R)
display(fr)
```

```python
fr.drop(fr[fr['Proportion']<0.0001].index , inplace=True)
fr.reset_index(drop=True, inplace= True)
print(len(fr), np.sum(fr['Proportion']))
display(fr)
```


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