รายงานวิจัย

เรื่อง

การสร้างแบบจำลองความผันผวนของราคารายชั่วโมงของตลาดหุ้นอสังหาริมทรัพย์ไทยโดยใช้การวิเคราะห์ GARCH

Modelling of Hourly Price Volatility of Thailand Property Stock Market Using GARCH Analysis

โดย
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การวิจัยครั้งนี้ได้รับเงินทุนการวิจัยจากมหาวิทยาลัยราชพฤกษ์

ปีการศึกษา 2566

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บทคัดย่อ

งานวิจัยนี้มีวัตถุประสงค์เพื่อตรวจสอบรูปแบบระหว่างวันของความผันผวนของราคารายชั่วโมงในตลาดหุ้นอสังหาริมทรัพย์ในประเทศไทย และประเมินประสิทธิผลของการวิเคราะห์ GARCH ในการจับรูปแบบเหล่านี้ นอกจากนี้ ยังพยายามประเมินว่าเหตุการณ์สำคัญทั้งทางเศรษฐกิจมหภาคและเฉพาะบริษัท ส่งผลต่อความผันผวนรายชั่วโมงอย่างไร การศึกษานี้กล่าวถึงช่องว่างในความรู้เกี่ยวกับปัจจัยที่มีอิทธิพลต่อความผันผวนของราคารายชั่วโมงในหุ้นอสังหาริมทรัพย์ของประเทศไทยและมีวัตถุประสงค์เพื่อให้ข้อมูลเชิงลึกที่สำคัญสำหรับการบริหารความเสี่ยงและการตัดสินใจลงทุน วิธีการนี้เป็นการคัดเลือกบริษัทอสังหาริมทรัพย์ที่มีรายได้สูงสุด 10 อันดับแรกในประเทศไทยในปี 2566 และใช้แบบจำลอง GARCH เพื่อวิเคราะห์ความผันผวน โดยเฉพาะอย่างยิ่ง แบบจำลอง GARCH(1,1) ถูกนำมาใช้เพื่อระบุลักษณะและคาดการณ์ความผันผวนของผลตอบแทนหุ้นเมื่อเวลาผ่านไป

การวิเคราะห์ความผันผวนของผลตอบแทนรายชั่วโมงตั้งแต่ปี 2019 ถึง 2023 เผยให้เห็นความผันผวนพื้นฐาน โดยระดับที่สูงขึ้นในช่วงเริ่มต้นการซื้อขายจะค่อยๆ ลดลงทุกๆชั่วโมง และถึงจุดสูงสุดอีกครั้งเมื่อใกล้สิ้นสุดการซื้อขาย สิ่งนี้บ่งชี้ว่ากิจกรรมการตลาดในช่วงแรกและความผันผวนลดลงในช่วงหลังของวัน การศึกษายังตรวจสอบรูปแบบความผันผวนที่เกี่ยวข้องกับการประกาศอัตราดอกเบี้ยในช่วงเวลาการซื้อขาย โดยพบว่ามีความผันผวนที่แตกต่างกันไปในชั่วโมงการซื้อขายและเหตุการณ์ต่างๆ รวมถึงความผันผวนของระดับความผันผวนพื้นฐาน ความอ่อนไหวต่อการเปลี่ยนแปลงในอดีต การคงอยู่ของความผันผวน และการเปลี่ยนแปลงของผลตอบแทน นอกจากนี้การวิจัยยังชี้ให้เห็นว่าการล้มละลายของ China Evergrande มีผลกระทบที่ไม่มีนัยสำคัญต่อผลตอบแทนระหว่างวันและความผันผวนตลอดทั้งวันซื้อขาย

คำสำคัญ: การสร้างแบบจำลอง ความผันผวนของราคา ตลาดหุ้นอสังหาริมทรัพย์ไทย การวิเคราะห์ GARCH

Research Title: Modelling of Hourly Price Volatility of Thailand Property Stock Market Using GARCH Analysis

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Abstract

This research aimed to investigate the intraday patterns of hourly price volatility in the Thailand Property Stock Market and evaluate the effectiveness of GARCH analysis in capturing these patterns. It also sought to assess how significant events, both macroeconomic and firm-specific, contributed to hourly volatility. The study addressed a gap in knowledge regarding the factors influencing hourly price volatility in Thailand's property stocks and aimed to provide insights crucial for risk management and investment decision-making. The methodology involved selecting the top 10 highest-earning property companies in Thailand in 2023 and applying the GARCH model to analyze volatility. Specifically, the GARCH(1,1) model was used to characterize and predict stock returns' volatility over time.

The analysis of intraday hourly returns volatility from 2019 to 2023 revealed fluctuating baseline volatility, with higher levels at the start of trading that gradually decreased throughout the session, peaking again near the end of trading. This suggests early market activity and volatility tapering off later in the day. The study also examined volatility patterns concerning interest rate announcements on trading hours. It found varying dynamics in volatility across different trading hours and events, including fluctuations in baseline volatility levels, sensitivities to past shocks, volatility persistence, and variation in returns. In addition, the research indicated that the China Evergrande bankruptcy had an insignificant effect on intraday returns and volatility throughout the trading day.

Keywords: Modelling, Price Volatility, Thailand Property Stock Market, GARCH Analysis

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Sethapong Watanapalachaikul

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Chapter 1
Introduction

The Thailand property stock market held a pivotal position within the country's financial landscape, reflecting the dynamic interplay between the real estate sector and capital markets. As one of Southeast Asia's economic powerhouses, Thailand witnessed significant growth and transformation in its property market, contributing to the vibrancy of its stock exchanges. A comprehensive understanding of the background and key characteristics of the Thailand property stock market was essential for researchers, investors, and policymakers aiming to navigate its complexities.

The outline structure of this chapter are as follows:

1.1 Background and Problem Statement
1.2 Research Questions
1.3 Research Objectives
1.4 Research Hypothesis
1.5 Research Scope and Limitation
1.6 Definition
1.7 Significance of the Study

1.1 Background and Problem Statement

The property sector in Thailand had long been a cornerstone of economic development. The market's significance extended beyond its role in providing housing and commercial spaces, as it played a crucial role in wealth creation, employment generation, and overall economic growth. The property stock market, therefore, served as a barometer of the broader economic health of the country. The Thailand property stock market was characterized by the presence of key players, including real estate development companies, property investment firms, and construction entities. Major stock exchanges, such as the Stock Exchange of Thailand

(SET), provided a platform for these companies to list and trade their stocks, allowing investors to participate in the real estate sector's growth (Amonhaemanon, 2014).

The regulatory framework governing the Thailand property stock market was designed to ensure transparency, fair practices, and investor protection. Regulatory bodies, including the Securities and Exchange Commission (SEC) of Thailand, oversaw the compliance of property-related companies with disclosure requirements, financial reporting standards, and corporate governance principles.

The Thailand property stock market experienced fluctuations influenced by various factors, including interest rates, economic indicators, government policies, and global market trends. The market's resilience and responsiveness to these dynamics made it an intriguing subject for researchers seeking to understand the correlation between real estate dynamics and financial market behavior.

Thailand had attracted significant foreign investment in its property market, with international investors seeking opportunities in residential, commercial, and hospitality developments. The globalization of the property stock market introduced elements of both risk and opportunity, as it was influenced not only by domestic factors but also by broader international economic conditions.

Recent years saw the emergence of new trends in the Thailand property stock market, including sustainable development practices, digitalization, and changing consumer preferences. Additionally, the market faced challenges such as regulatory uncertainties, fluctuations in property values, and the impact of external shocks, as exemplified by the challenges posed by the COVID-19 pandemic.

While there was a body of literature on the Thailand property market, there remained gaps in understanding the intricacies of the property stock market, especially on an hourly basis. Investigating the volatility patterns and risk factors in this market through advanced econometric models like GARCH analysis could provide valuable insights for investors and policymakers, enhancing the overall comprehension of the market's behavior.

The research problem that was addressed involved the modeling of hourly price volatility within the Thailand Property Stock Market through the application of GARCH analysis. Despite existing studies on volatility modeling in financial markets, there was a recognized gap in knowledge pertaining to the specific factors influencing hourly price volatility in the context of Thailand's property stocks. The research aimed to address this gap by investigating the intricate dynamics and patterns associated with hourly price volatility in the Thailand Property Stock Market, utilizing GARCH analysis as the primary analytical tool. The identification and understanding of these factors were crucial for developing accurate and reliable models that could contribute to effective risk management and investment decision-making in this specific financial market.

In conclusion, understanding the nuanced background of the Thailand property stock market was crucial for researchers seeking to contribute to the field, policymakers aiming to implement effective regulations, and investors looking to make informed decisions in this dynamic and influential sector.

1.2 Research Questions

This research is guided by the following key research questions:

1.2.1 How do intraday patterns of hourly price volatility manifest within the Thailand Property Stock Market, and how can GARCH analysis capture and explain these patterns?

1.2.2 To what extent do significant events, both macroeconomic (such as interest rate) and firm-specific (such as a bankruptcy of China Evergrande Group), drive hourly price volatility in the Thailand Property Stock Market, as modeled using GARCH analysis?

1.3 Research Objectives

The primary objectives of this research paper are:

1.3.1 To identify and analyze the intraday patterns of hourly price volatility in the Thailand Property Stock Market and to assess the effectiveness of GARCH analysis in capturing and explaining the observed intraday volatility patterns.

1.3.2 To utilize GARCH analysis to model and quantify the extent to which significant events, both macroeconomic and firm-specific events contribute to hourly volatility.

1.4 Research Hypothesis

This research is assumed by following hypotheses:

1.4.1 There exists a significant intraday pattern in the hourly price volatility within the Thailand Property Stock Market.

1.4.2 GARCH analysis is effective in providing a statistically significant explanation for the observed intraday volatility patterns influenced by macroeconomic and firm-specific events in the market.

1.5 Research Scope and Limitation

This study aims to comprehensively investigate the hourly price volatility of the Thailand property stock market through GARCH analysis during 2019 to 2023. The scope of this research encompasses the examination of various factors contributing to price volatility, including market dynamics, economic indicators, and regulatory influences. Additionally, the study intends to explore the implications of volatility patterns on investment strategies, market efficiency, and risk management within the Thailand property stock market context.

Despite the rigorous methodology employed in this research, certain limitations warrant acknowledgment. Firstly, the analysis relies on historical data during 2019 to 2023, which may not fully capture current market conditions or unforeseen events. Secondly, the GARCH model, while widely utilized, is based on certain assumptions that may not always hold true in real-world scenarios, potentially impacting the accuracy of volatility forecasts. Additionally, the scope of this study is limited to the Thailand property stock market, thereby restricting generalizability to other financial markets or asset classes. Furthermore, the interpretation of results is subject to inherent uncertainties and the presence of exogenous factors beyond the scope of this research. These limitations underscore the need for cautious interpretation and further research to enhance the robustness of findings and broaden the applicability of the analysis.

1.6 Definition

Modelling, Price Volatility, Thailand Property Stock Market

Modelling – Econometric modeling refers to the application of statistical and mathematical techniques to analyze and quantify relationships within economic systems. It involves the construction of mathematical models that aim to capture the complex interactions and dependencies among various economic variables. These models are designed to represent and explain the behavior of economic phenomena, facilitating the testing of hypotheses, forecasting future trends, and making informed policy or business decisions. Econometric modeling typically incorporates data from empirical observations, and through the estimation of model parameters, it seeks to provide insights into the underlying economic mechanisms governing the relationships among variables. The ultimate goal is to enhance our understanding of economic processes, allowing for more accurate predictions and informed decision-making in economic analysis and policy formulation.

Price Volatility – Price volatility refers to the degree of variation or fluctuation in the price of a financial instrument, commodity, or asset over a specific period. It is a statistical measure that quantifies the extent of price movements, indicating the degree of uncertainty or risk associated with an investment. Higher volatility implies larger and more frequent price changes, while lower volatility suggests a more stable and predictable price environment. Price volatility is a crucial concept in financial markets, influencing investment strategies, risk management decisions, and the overall assessment of market conditions. Various statistical models, such as the standard deviation or the use of volatility indices, are employed to measure and analyze price volatility in different financial instruments.

Thailand Property Stock Market – Thailand Property Stock Market conveys the notion of a segment within the broader financial market of Thailand, focusing on publicly traded companies involved in real estate and property development. In this context, the term encapsulates the intersection of the stock market and the real estate sector, where shares of companies engaged in property-related activities are bought and sold. This implies a specific financial niche wherein investors can participate in the performance and growth of the Thai real estate industry through equities trading.

GARCH Analysis – GARCH (Generalized Autoregressive Conditional Heteroskedasticity) analysis is a statistical method in financial econometrics that models and analyzes time series data, specifically focusing on volatility. Developed by Robert Engle, GARCH models incorporate an autoregressive component to account for the persistence of volatility and a conditional heteroskedastic component to recognize that volatility varies based on past information. The main objective of GARCH analysis is to estimate model parameters, providing insights into the underlying volatility patterns within a time series. Widely used in finance, GARCH models are valuable for risk management, option pricing, and forecasting future volatility, offering a flexible framework for capturing the dynamic nature of financial market volatility.

1.7 Significance of the Study

The research on modeling hourly price volatility in the Thailand Property Stock Market during 2019 to 2023, using GARCH analysis holds paramount significance across various domains. It plays a crucial role in advancing risk management strategies, aiding investment decision-making, informing policy formulation, enhancing market efficiency and transparency, contributing to academic knowledge, enabling real-time forecasting, and guiding risk-aware business strategies.

The study's implications span from empowering investors and policymakers to fostering market stability and influencing real-time decision-making processes. Overall, the research has far-reaching implications, making notable contributions to both academia and practical applications in the financial landscape.

In conclusion, the research on the modelling of hourly price volatility in the Thailand Property Stock Market using GARCH analysis transcends academic realms and holds substantial implications for practitioners, policymakers, and market participants. The multifaceted significance of this research underscores its potential to reshape decision-making processes, foster market stability, and contribute to the advancement of financial knowledge.

Chapter 2
Literature Review

This chapter provides with an overview of the theoretical underpinnings of GARCH modeling, elucidating its relevance and applicability in financial econometrics. The literature review aims to comprehensively explore existing research, discussing theoretical foundations, relevant concepts, and related literature. By identifying gaps and inconsistencies between literatures, it aims to contribute to the advancement of financial econometrics and enhance our understanding of volatility within the Thailand property stock market.

The outline structure of this chapter are as follows:

2.1 Theoretical Framework

2.2 Review of Related Literature

2.3 Conceptual Framework

2.1 Theoretical Framework

A substantial body of literature underscored the efficacy of GARCH models in capturing volatility patterns in financial markets. Engle (1982) and Bollerslev (1986) pioneered the development of GARCH, highlighting its ability to model time-varying volatility and providing a valuable tool for risk management and financial forecasting.

The examination of relative volatility in financial time series, encompassing stock prices and returns, was a contentious subject within empirical finance. Conflicting and contradictory empirical evidence emerged regarding whether the stock market exhibited excessive volatility. Moreover, the selection of models for investigating volatility was a topic of contention, and the literature on volatility remained inconclusive. Volatility modeling in the emerging financial markets, especially within the stock exchange market, garnered increasing interest from academics in recent years. It functioned as a fundamental risk measure in asset pricing models and unquestionably, proved immensely valuable in applications such as pricing stocks and derivatives. The examination of volatility in the stock market played a pivotal role in portfolio and risk management. A comprehensive comprehension of volatility was highly advantageous for investors in the stock market, as elevated volatility could signify remarkable gains or losses, thus amplifying uncertainty.

There existed a plethora of volatility models utilized in the financial industry. These models and tests were broadly categorized under three distinct groups: 1) variance bound tests; 2) cointegration-related VAR methods; and 3) ARCH and GARCH models predicated on a time-varying risk premium (Mills 1999; Cuthbertson 1996). Owing to the issues associated with tests delineated in types 1 and 2 aforementioned, coupled with the comprehensiveness of these tests in identifying excessive volatility, the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH) models were deemed suitable and saw increasing utilization to scrutinize the presence of excessive volatility in recent years. Several models gained acceptance and widespread use, including ARCH and GARCH models, ARMA and ARIMA models, and Stochastic Volatility (SV) models. Additionally, straightforward measures such as standard deviation found application in empirical finance (Islam & Oh 2003).

Despite the existence of literature on forecasting volatility with various types of models, consensus regarding the optimal volatility model was not reached among financial experts. Yu (2002) asserted that no single superior model existed for analyzing and forecasting volatility. Consequently, different stock analysts, with differing expectations and positions, may have had distinct preferences and perspectives on defining volatility risk and selecting appropriate volatility models. ARCH and GARCH type models were adopted due to their advantages and suitability. ARCH and GARCH type models could be used in both linear and non-linear variants. These models were used for identifying and predicting volatility in stock prices and seasonal anomalies in Thailand.

For a volatility model to be considered reliable, it was required to offer accurate risk or volatility outcomes across various assets, time frames, and risk levels within the same asset class (Danielsson, 2002). Notable examples of evaluations and comparisons between volatility models included the studies conducted by Aydemir (1998), Brooks et al. (2000), Barndorff-Nielsen et al. (2001), Hansen & Lunde (2001), Poon & Granger (2003).

2.1.1 Estimating and Forecasting the Financial Market Volatility

The utilization of univariate parametric models such as GARCH type models in the estimation and forecasting of financial market volatility experienced a surge in popularity, particularly in the context of dealing with incomplete or emerging financial markets, as observed in Thailand. One of the most commonly utilized modified ARCH models was the Generalized ARCH (GARCH) model, remodeled by Bollerslev (1986). Other ARCH-type models were characterized by Nelson (1991), who introduced the Exponential GARCH (EGARCH). Glosten et al. (1993) developed the GJR-GARCH(p,q) model to estimate the relationship between the expected value and the volatility of nominal excess returns on stocks. Ding et al. (1993) extended the ARCH class of models to identify a broader class of power transformations, termed Power Generalized ARCH or PGARCH.

These models comprised both linear and non-linear types, with non-linear models including EGARCH, GJR-GARCH, and PGARCH. Franses & Dijk (2000) concluded that linear time series models did not produce reliable forecasts. However, this did not imply that linear models were not useful, as they were utilized in comparing results for the index price of various stock exchanges.

2.1.2 GARCH(p,q)

In empirical applications of the ARCH(q) model, it was often difficult to estimate models with a large number of parameters. This motivated Bollerslev (1986) to use the Generalized ARCH or GARCH(*p*,*q*) specification to circumvent this problem. The GARCH(*p*,*q*) model is defined as:

$$r_t = \mu + \sigma_t \varepsilon_t$$

and:

$$\sigma_t^2 = \lambda + \sum_{i=1}^{q} \alpha_i (r_{t-i} - \mu)^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \ .$$

The model could also be represented as:

$$\sigma_t^2 = \lambda + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

or:

$$\sigma_t^2 = \lambda + \alpha(L)\varepsilon_{t-1}^2 + \beta(L)\sigma_{t-1}^2 .$$

A sufficient condition for conditional variance in the GARCH(*p*,*q*) model to be well defined is that all the coefficients in the infinite order linear ARCH model must be positive. Given that $\alpha(L)$ and $\beta(L)$ have no common roots and that the roots of the polynomial in L, $1 - \beta(L) = 0$ lie outside the unit circle, this positive constraint is satisfied, if and only if, the coefficients of the infinite power series expansion for $\frac{\alpha(L)}{1-\beta(L)}$ are non-negative.

Rearranging the GARCH(*p*,*q*) model by defining $v_t \equiv \varepsilon_t^2 - \sigma_t^2$, it follows that:

$$\varepsilon_t^2 = \lambda + (\alpha(L) + \beta(L))\varepsilon_{t-1}^2 - \beta(L)v_{t-1} + v_t$$

which defines an ARMA (Max(*p*,*q*),*p*) model for ε_t^2.

In addition, the model is covariance stationary if and only if all the roots of $(1-\alpha(L)-\beta(L))$ lie outside the unit circle. If all the coefficients are non-negative, this is equivalent to the sum of the autoregressive coefficients being smaller than 1. The analogy to the ARMA class of models also allows for the use of standard time series techniques in the identification of the order of *p* and *q*. In most empirical applications with finitely sampled data, the simple GARCH(1,1) is found to provide a fair description of the data.

The GARCH(1,1) is used to construct multi-period forecasts of volatility. When $\alpha + \beta < 1$, the unconditional variance of ε_{t+1} is $\frac{\lambda}{1-\alpha-\beta}$. If we rewrite the following GARCH(1,1) as:

$$\begin{aligned}\sigma_t^2 &= \lambda + \alpha(\varepsilon_{t-1}^2) + \beta(\sigma_{t-1}^2) \\ &= \lambda + \alpha(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\alpha + \beta)\sigma_{t-1}^2 .\end{aligned}$$

The coefficient measures the extent to which the impact of volatility will extend into the next period’s volatility, while $(\alpha + \beta)$ measures the rate at which this effect reduces over time. Recursively substituting and using the law of iterated expectation, the conditional expectation of volatility *j* periods ahead is:

$$E_t[\sigma_{t+j}^2] = (\alpha+\beta)^j \left[\frac{\sigma_t^2 - \lambda}{1-\alpha-\beta}\right] + \left[\frac{\sigma_t^2 - \lambda}{1-\alpha-\beta}\right].$$

note that the multi-period volatility forecast reverts to its unconditional mean at rate $(\alpha+\beta)$.

2.2 Review of Related Literature

2.2.1 Application of GARCH in Real Estate Markets

While GARCH models had been extensively applied in financial markets, their application to real estate markets, particularly in the context of daily and hourly price volatility, was relatively underexplored. Engle (1982) formulated a model to characterize time-varying variance, known as Autoregressive Conditional Heteroscedasticity (ARCH). The inception of the ARCH model concept precipitated the emergence of related formulations aimed at discerning and elucidating the variance of time series. Engle introduced the linear ARCH(q) model, which posits that the time-varying conditional variance is a linear function of the past q squared innovations. The ARCH(q) model is defined by:

$$r_t = \mu + \sigma_t \varepsilon_t$$

and:

$$\sigma_t^2 = \lambda + \alpha_1 (r_{t-1} - \mu)^2 +, \ldots, + \alpha_q (r_{t-q} - \mu)^2$$

where r_t is the stock market returns, μ is the conditional mean of the return process and is constant, $\varepsilon_t \sim NID(0,1)$ is conditionally Gaussian (NID denotes normally and independently distributed), σ_t is the first alternative of the stochastic volatility models and is modelled by a stochastic process, λ_1 and α are real constants, and ε_t are zero mean, uncorrelated, random variables or white noise.

The model could also be represented as:

$$\sigma_t^2 = \lambda + \sum \alpha_1 r_{t-1}^2 + \varepsilon_t .$$

Hence the volatility σ_{t+1}^2 can be represented by:

$$\sigma_{t+1}^2 = E((r_{t+1} - \mu)^2 \mid \Phi_t)$$

$$\sigma_{t+1}^2 = \lambda + \alpha_1 (r_{t-1} - \mu)^2 +, \ldots, + \alpha_q (r_{t-q} - \mu)^2$$

where Φ_t is the information set at the end of period t.

This is an $AR(q)$ model in terms of $(r_t - \mu)^2$. Therefore, the optimal one-day ahead forecast of period $t+1$ volatility can be obtained based on the returns on the most recent q days. In general, an h-day ahead step forecast can be formed as follows:

$$\hat{\sigma}^2_{t+h} = \lambda + \alpha_1(\hat{r}_{t+h-1} - \mu)^2 +,\ldots,+\alpha_q(\hat{r}_{t+1-q} - \mu)^2$$

where $\hat{r}_{t+h-1} = r_{t+h-j}$ if $1 \le h \le j$ and ($\hat{\sigma}^2_{t+h-j} = (\hat{r}_{t+h-1} - \mu)^2$ if $h > j$.

The ARCH (1) Model

This simple ARCH model exhibits constant unconditional variance but non-constant conditional variance.

$$r_t = \mu + \sigma_t \varepsilon_t$$

given that:

$$\varepsilon_t = u_t \sqrt{(\lambda + \alpha\varepsilon^2_{t-1})}$$

where $u_t \sim IID(0,1)$ (IID, Independent and Identically Distributed, or strict white noise); and λ and $\alpha > 0$. Note that $\sqrt{(\lambda + \alpha\varepsilon^2_{t-1})}$ is the conditional standard deviation; and σ_t is defined as:

$$\sqrt{E(\varepsilon^2_t \mid \varepsilon^2_{t-1}, \varepsilon^2_{t-2}, \ldots, \varepsilon^2_{t-i})}\,.$$

The simplest form of ARCH (1) model for the: *conditional expectation* of ε_t given that ε_t is equal to zero, is defined as:

$$E(\varepsilon_t \varepsilon_{t-1}) = E(u_t \mid \varepsilon_{t-1})\sqrt{\lambda + \alpha\varepsilon^2_{t-1}} = 0$$

note that $E(u_t \mid \varepsilon_{t-1}) = E(u_t) = 0$ since $u_t \sim IID(0,1)$;

Conditional variance is defined as:

$$Var(\varepsilon_t \mid \varepsilon_{t-1}) = E(u^2_t \mid \varepsilon_{t-1})(\lambda + \alpha\varepsilon^2_{t-1})$$

note that $E(u^2_t \mid \varepsilon_{t-1}) = E(u^2_t) = 1$ since $u_t \sim IID(0,1)$.

Thus, the conditional mean and variance of r_t are given by the following formulae:

$$E(r_t \mid r_{t-1}) = \mu$$

and:

$$Var(r_t \mid r_{t-1}) = (\lambda + \alpha\varepsilon^2_{t-1})\,.$$

Therefore, the conditional variance of r_t is time varying. However, it can be easily seen that the unconditional variance is time invariant given that ε_t^2 is stationary:

$$Var(r_t) = Var(\varepsilon_t) = \frac{\lambda}{(1-\alpha)}.$$

First Order Autoregressive Process with ARCH Effects

For more complicated models such as AR(1)-ARCH(1), it is possible to obtain similar results provided that the process for *t* is stationary given that the autoregressive parameter is smaller than one in absolute value.

Assume the following first order autoregressive process:

$$r_t = \theta r_{t-1} + \varepsilon_t$$

where $\varepsilon_t = u_t\sqrt{\lambda + \alpha\varepsilon_{t-1}^2}$, $u_t \sim$ IIN(0,1), and $\lambda > 0$, $\alpha = 0$.

a) The conditional expectation of ε_t given that ε_t is equal to zero is:

$$E(\varepsilon_t \varepsilon_{t-1}) = E(u_t^2 \mid \varepsilon_{t-1})(\lambda + \alpha\varepsilon_{t-1}^2) = 0$$

note that $E(u_t \mid \varepsilon_{t-1}) = E(u_t) = 0$.

b) The *conditional variance* is given by the following formula:

$$Var(\varepsilon_t \mid \varepsilon_{t-1}) = E(u_t^2 \mid \varepsilon_{t-1})(\lambda + \alpha\varepsilon_{t-1}^2) = \lambda + \alpha\varepsilon_{t-1}^2$$

note that $E(u_t^2 \mid \varepsilon_{t-1}) = E(u_t) = 1$ since $u_t \sim$ IIN(0,1).

Then the conditional mean and variance of r_t are given by the following formulae:

$$E(r_t \mid r_{t-1}) = \theta r_{t-1}$$

and:

$$Var(r_t \mid r_{t-1}) = (\lambda + \alpha\varepsilon_{t-1}^2).$$

To find the unconditional variance of r_t , recalling the following property for the variance:

$$Var(r_t) = E(Var(r_t \mid r_{t-1})) + Var(E(r_t \mid r_{t-1})).$$

The left hand-side formula $E(Var(r_t \mid r_{t-1}))$ is equal to $E(\lambda + \alpha\varepsilon_{t-1}^2)$, $\lambda + \alpha E(\varepsilon_{t-1}^2)$ and $\lambda + \alpha Var(\varepsilon_{t-1})$. The right hand-side formula $Var(E(r_t \mid r_{t-1}))$ is equal to $\theta^2 Var(r_{t-1})$. Then if the process is covariance stationarity, it is formulated as:

$$Var(r_t) = \frac{\lambda + \alpha Var(\varepsilon_{t-1})}{1-\theta^2}$$

or:

$$Var(r_t) = \frac{1}{(1-\alpha)(1-\theta^2)}$$

since:

$$Var(\varepsilon_{t-1}) = \frac{\lambda}{(1-\alpha)} .$$

According to Aydemir (1998), the important property of ARCH models is their ability to capture the tendency for volatility clustering in stock prices data, i.e. a tendency for large or small swings in prices to be followed by large or small swings in random direction. In addition, Aydemir (1998) also found that the ARCH/GARCH type models are significantly outperformed by other models including the ARMA and SV models. The study by Chen & Liu (2009) stood out as a pioneering effort in applying GARCH models to real estate prices, but the focus was on daily data rather than hourly intervals.

2.2.2 Intraday Volatility Patterns

Previous studies examining intraday volatility patterns in financial markets offered insights into the relevance of hourly analysis. Schwert (1990) and Poon & Granger (2003) demonstrated the presence of intraday volatility patterns, suggesting that hourly modeling is essential for understanding short-term market dynamics. Autoregressive Moving Average (ARMA) Models was used to identify intraday volatility patterns in stock markets. Referring to ARMA models where autoregressive in order p, [AR(p)] can be expressed as:

$$y_t = \gamma_1(y_{t-1}) + \gamma_2(y_{t-2}) +,\ldots,+ \gamma_p(y_{t-p}) + \varepsilon_t$$

where y_t = the actual or data value at time t, γ = the constant value, and ε_t = the residual or error term.

Moving average of order q, [MA(q)] can be expressed as:

$$y_t = \varepsilon_t - \theta_1(\varepsilon_{t-1}) - \theta_2(\varepsilon_{t-2}) -,\ldots,- \theta_q(\varepsilon_{t-q}) .$$

The general presentation for ARMA models is:

$$y_t = \gamma_{0,1} + \sum_{j=1}^{p} \gamma_j y_{t-j} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \; .$$

These models were widely used in the finance literature especially during the last decade. Some studies such as Schwert (1990), French et al., (1987), and Poterba & Summer (1986) use the ARMA process for modelling intraday volatility of the stock market. According to Aydemir (1998), the advantages of these models included the following: 1) the theory of the Gaussian model was well understood, therefore, the ARMA models were well developed; 2) modeling data within an ARMA structure was considerably easy; and 3) these models were capable of data analysis, forecasting, and control. However, several limitations of the ARMA models were identified, including: 1) the models had definite limitations in mimicking the properties where sudden bursts of data at irregular time intervals and periods of high and low volatility were detected, such as the data of the stock returns covering period during economic crisis; and 2) the ARMA type models were based on the assumption of constant variance. Most financial data exhibited changes in volatility, and this feature of the data could not be captured due to this assumption.

Jiang (1998) utilized SV model to detect intraday volatility of the stock market. There were several types of Stochastic Volatility (SV) models, one the most popular being the discrete-time SV model, the continuous-time SV model and the jump diffusion model with SV. The relevant type of SV model applicable to stock market data is the discrete-time SV model, where s_t denotes the stock price at time t and the detrended return process y_t is defined as (Jiang 1998):

$$y_t = \ln\left(\frac{s_t}{s_{t-1}}\right) - \mu_t \, .$$

The SV model of stock return may be written as:

$$y_t = \sigma_t \varepsilon_t$$

where $\varepsilon_t \sim IID$. The most popular SV specification assumes that h_t follows an AR(1) process as:

$$h_{t+1} = \phi h_t + \eta_t \, , \; |\phi| < 1$$

where η_t is an innovation. This process is satisfied using the idea of Exponential GARCH (EGARCH) and this specification ensures that the conditional variance remains positive.

According to Barndorff-Nielsen et al., (2001) and Aydemir (1998), there were several advantages in using SV models. SV properties could be found and manipulated much easier than ARCH/GARCH type models, and they could also mimic the fat tail property observed in the data. Finally, they also induced an incomplete market. However, Hansen & Lunde (2001) disagreed that these SV models were superior to the ARCH/GARCH type model when using returns of stock indices or bonds. Furthermore, in SV models, the persistence in volatilities could be captured by specifying a random walk process. This specification was analogous to the IGARCH specification.

2.2.3 Macroeconomic Influences on Volatility

Research addressing the impact of macroeconomic factors on volatility was pertinent to the proposed study. Yiu et al. (2013) investigated the relationship between interest rates and real estate volatility, establishing a foundation for understanding the macroeconomic drivers of volatility in property markets.

Yui et al. (2013) posited a model that detected relationship between the mean of a return and its variance such as interest rates and real estate volatility by incorporating this relationship was to explicitly model returns as a function of the conditional variance, essentially treating the conditional variance as an additional regressor. The GARCH in Mean Model (GARCH-M) was designed to accommodate the possibility of mean effects on the conditional variance. Typically, the conditional variance term in this model is interpreted as representing time-varying risk premiums. Recall the equation:

$$\begin{aligned} \sigma_t^2 &= \lambda + \alpha(\varepsilon_{t-1}^2) + \beta(\sigma_{t-1}^2) \\ &= \lambda + \alpha(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\alpha + \beta)\sigma_{t-1}^2 \end{aligned}$$

and ARCH-M:

$$r_t = \psi\sigma_t^2 + \varepsilon_t$$

where $\varepsilon_t = v_t \sigma_t$, and $v_t \sim N(0,1)$:

$$\sigma_t^2 = w + \lambda + \alpha \varepsilon_{t-1}^2 .$$

Then r_t may be expressed as:

$$r_t = \psi(\lambda + \alpha \varepsilon_{t-1}^2) + \varepsilon_t .$$

Consider the following formula (extension form of the above equation):

$$r_t = \theta x_t + \psi \sigma_t^2 + \varepsilon_t .$$

Therefore, GARCH-M could be defined as:

$$\sigma_t^2 = \lambda + \alpha(L) \varepsilon_{t-1}^2 + \beta(L) \varepsilon_{t-1}^2 .$$

Consistent estimation of θ and ψ is dependent on the correct specification of the entire model. The estimation of GARCH in mean type of models was numerically unstable and many empirical applications have used the ARCH-M type of models which are easier to estimate.

a) The Effect of COVID-19 Pandemic toward Property Sector

The COVID-19 pandemic began in December 2019 when cases of a novel coronavirus were first reported in Wuhan, Hubei province, China. Since then, COVID-19 has rapidly spread globally, leading to widespread illness, significant loss of life, and unprecedented societal and economic disruptions. The COVID-19 pandemic had profound effects on the property industry, exerting significant influence across various sectors, including residential, commercial, and industrial real estate. The pandemic prompted notable shifts in demand for different property types. With the widespread adoption of remote work, there was a surge in demand for properties offering increased space, such as suburban homes equipped with dedicated home offices and outdoor areas. Conversely, demand for commercial real estate, particularly office spaces in urban centers, declined as companies embraced remote or hybrid work arrangements (Cui, 2023).

Rental markets experienced varying impacts based on geographical location and property type. In some regions, reduced demand for rental properties ensued due to economic uncertainty and job losses, resulting in decreased rental prices.

However, other areas witnessed sustained rental demand, notably in suburban locales where individuals sought enhanced space and amenities (Allan et al., 2021).

The pandemic precipitated delays in construction projects owing to enforced shutdowns, labor scarcities, and disruptions in supply chains. Consequently, project timelines extended and costs escalated for developers, affecting both residential and commercial real estate development endeavors (Allan et al., 2021).

Governments worldwide implemented diverse policies and support measures to mitigate the pandemic's repercussions on the property industry. These interventions ranged from eviction moratoriums and rent relief programs to incentives for homebuyers and developers. The efficacy of these measures varied depending on local contexts and implementation strategies (Cui, 2023).

Investment patterns in the property industry underwent transformations in response to the pandemic. Some investors redirected their focus toward property sectors deemed resilient to economic downturns, such as multifamily residential properties and industrial real estate (e.g., warehouses and distribution centers). Concurrently, investments in sectors like hospitality and retail real estate dwindled significantly, reflecting their pronounced vulnerability to lockdowns and restrictions.

The pandemic accelerated the adoption of technology within the property industry, particularly in areas such as virtual property tours, digital transactions, and remote property management. These technological strides are poised to have enduring implications for real estate transactions and property management practices in the post-pandemic landscape (Cui, 2023).

In summation, the COVID-19 pandemic presented formidable challenges to the property industry while catalyzing transformative changes and innovations that are likely to shape its trajectory in the aftermath of the crisis.

b) FOMC Meeting Policy and Property Sector

The Federal Open Market Committee (FOMC) meetings, convened by the Federal Reserve in the United States, exerted discernible effects on the property industry owing to their influence on monetary policy. The effects are expounded as follows (Gurkaynak et al., 2007):

Interest Rates: A principal instrument of monetary policy, the adjustment of interest rates, was scrutinized following FOMC meetings. Decisions regarding alterations in the federal funds rate, representing the rate at which banks lend to each other overnight, were disseminated. Alterations in interest rates could directly affect borrowing costs for individuals and businesses in the property sector. Lower interest rates were prone to stimulating demand for real estate by rendering mortgages and other financing instruments more affordable. Conversely, elevated interest rates could have tempered demand for property by heightening borrowing expenses (Rigobon, 2024).

Mortgage Rates: Decisions made by the FOMC regarding interest rates were equally influential on mortgage rates. Mortgage rates typically trailed movements in the federal funds rate, although other factors such as inflation expectations and investor demand for mortgage-backed securities also exerted influence. Changes in mortgage rates could have impacted home affordability and purchasing decisions, thereby influencing the residential property market (Lucca & Moench, 2015).

Investor Sentiment: The pronouncements of the FOMC meetings could have influenced investor sentiment and market expectations. Anticipation of adjustments in interest rates or other monetary policy measures could have induced volatility in financial markets, including the real estate sector. Investors might have revised their investment strategies in response to FOMC decisions, potentially affecting property prices and market dynamics (Rigobon, 2024).

Asset Prices: Monetary policy changes could have had broader repercussions on asset valuations, including real estate. Lower interest rates might have prompted investors to seek higher-yielding assets like real estate, potentially propelling property prices upwards. Conversely, higher interest rates could have diminished investor appetite for real estate, potentially exerting downward pressure on property valuations (Rigobon, 2024).

Commercial Real Estate Financing: FOMC decisions also influenced financing conditions for commercial real estate ventures. Alterations in interest rates and market sentiment could have affected the availability and cost of financing for commercial projects, thereby influencing investment and development activity within the commercial property sector (Lucca & Moench, 2015).

In summation, FOMC meetings and the decisions regarding monetary policy had pronounced ramifications on the property industry by virtue of their impacts on interest rates, mortgage rates, investor sentiment, asset valuations, and commercial real estate financing conditions. Consequently, participants within the property industry closely monitored FOMC announcements and adapted their strategies in response to shifts in monetary policy.

c) Interest Rate Changes in Thailand

The interest rate decisions announced by the Bank of Thailand from 2019 to 2023 provided valuable insights into the monetary policy landscape during that period.

The data revealed a series of adjustments in interest rates, reflecting the Bank's responses to prevailing economic conditions and policy objectives. Notably, fluctuations in interest rates occurred over time, with adjustments made in response to changes in economic indicators such as inflation, economic growth, and financial stability (see Figure 2.1).

For instance, from November 2019 to February 2020, interest rates remained stable at 1.25%. This period coincided with relatively stable economic conditions, where the Bank likely aimed to maintain a supportive monetary policy stance to stimulate economic growth while ensuring price stability.

However, as the COVID-19 pandemic emerged and began to impact the global economy, the Bank of Thailand responded by implementing monetary easing measures. This was evident in the reduction of interest rates from 1.25% in February 2020 to 0.50% by June 2020. These rate cuts were aimed at providing liquidity support to businesses and households, mitigating the economic fallout from the pandemic.

Following this period of aggressive monetary easing, interest rates remained at historically low levels throughout 2021 and 2022, ranging from 0.50% to 0.75%. This accommodative monetary policy stance was intended to support economic recovery efforts and facilitate borrowing and spending to stimulate demand.

Moreover, the interest rate decisions in 2023, particularly the announcements in September and November, indicated a cautious approach by the Bank of Thailand in managing monetary policy amidst evolving economic conditions. Despite the challenges posed by inflationary pressures and global uncertainties, the Bank maintained interest rates at 2.50%, suggesting a balanced approach to supporting economic growth while addressing inflationary concerns.

In summary, the interest rate decisions made by the Bank of Thailand from 2019 to 2023 reflected its efforts to navigate through a complex economic environment characterized by both domestic and global challenges. These decisions underscored the importance of monetary policy in supporting economic stability and fostering sustainable growth.

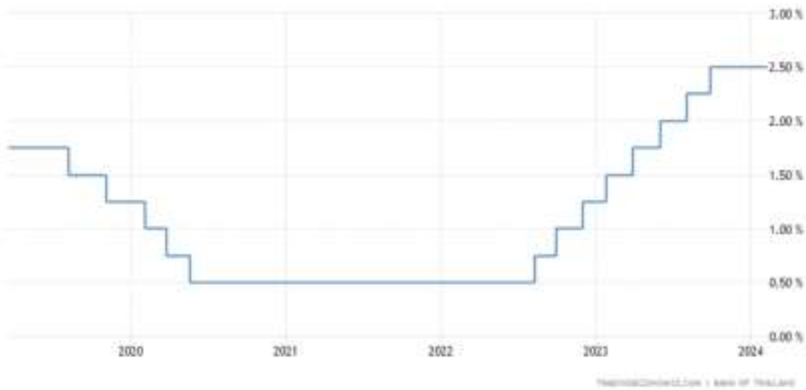


Figure 2.1 Thailand Interest Rate, 2019-2023

Source: tradingeconomics.com (2024)

2.2.4 Firm-Specific Events and Volatility

Examining the influence of firm-specific events on hourly price volatility was a crucial aspect. The bankruptcy of major real estate players, such as China Evergrande Group, had implications for volatility. The study by Yan (2023) provided insights into the impact of firm-specific news on real estate stock prices.

Even though the GARCH model has the capability to capture thick tailed returns, volatility clusterings are not well suited to capture the leverage effect since the conditional variance is a function only of the magnitudes of the lagged residuals and not their signs. Nelson (1991) introduced the exponential GARCH (EGARCH) where σ_t^2 depends on both the sign and the size of lagged residuals.

The EGARCH(1,1) model is represented as follows:

$$\ln\sigma_t^2 = \lambda_1 + \beta_1 \ln\sigma_{t-1}^2 + \gamma_1\left(\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - (2/\pi)^{1/2}\right] + \delta\left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right]\right).$$

Moreover, the EGARCH model possesses the capability to capture any asymmetric impact of shocks on volatility. This model permits volatility to be influenced differently by positive and negative news. In fact, the EGARCH model always produces a positive conditional variance σ_t^2 for any choice of λ_1, β_1, γ_1 so that no restrictions need to be placed on these coefficients (except $|\beta_1|<1$). Because of the use of both $|\varepsilon_t/\sigma_t|$ and $(\varepsilon_t/\sigma_t), \sigma_t^2$, it will also be non-symmetric in ε_t and, for negative δ, it will exhibit higher volatility for large negative ε_t. In conclusion, this model allows volatility to be influenced differently by positive and negative news on firm-specific events.

a) China Evergrande Bankruptcy

Prior to its collapse, Evergrande Group was among the largest real estate developers in China, holding a significant position in the country's property market. In 2021, Evergrande defaulted on its debt, which led to a property crisis in China's economy. The repercussions of this event continue to resonate. By the end of June the same year, the Shenzhen-based developer had amassed total liabilities of 2.39 trillion yuan ($333 billion), underscoring its considerable size and impact within the industry.

Consequently, Evergrande filed for bankruptcy in New York in 2023. On January 29th 2024, a Hong Kong court ordered the liquidation of China Evergrande Group, a development likely to reverberate through China's faltering financial markets as policymakers worked urgently to contain the escalating crisis. Trading in shares of China Evergrande, China Evergrande New Energy Vehicle Group, and Evergrande

Property Services were halted. Meanwhile, the benchmark Hang Seng Index experienced a slump in price (Reuters, 2024).

2.2.5 Empirical Studies in the Thai Context

A limited number of empirical studies specifically focusing on the Thailand Property Stock Market using GARCH analysis existed. The work by some researchers, such as Nguyen (2015), shed light on broader market dynamics, but the focus on hourly volatility remained an area warranting further exploration.

The use of univariate parametric models such as ARCH and GARCH-type models in estimating and forecasting financial market volatility experienced a surge in popularity, particularly in dealing with incomplete or emerging financial markets such as in Thailand. One of the most commonly employed modified ARCH models was the Generalized ARCH (GARCH) model developed by Engle (1982) and Bollerslev (1986). Other ARCH-type models included those characterized by Nelson (1991), who introduced the Exponential GARCH (EGARCH). Additionally, Glosten et al., (1993) developed the GJR-GARCH(p,q) model to estimate the relationship between the expected value and the volatility of nominal excess returns on stocks. Ding et al., (1993) proposed a model that extended the ARCH class of models to identify a broader class of power transformations, referred to as Power Generalized ARCH or PGARCH.

Nguyen (2015) implemented models comprised both linear and non-linear types, with non-linear models such as EGARCH, GJR-GARCH, and PGARCH being prominent for accessing volatility of the Thai property stock market. Franses and Dijk (2000) concluded that linear time series models did not yield reliable forecasts. However, this did not imply that linear models were not useful, as they were utilized in comparing results for the index price of the Stock Exchange of Thailand.

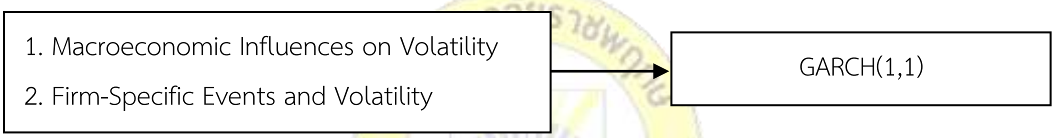
The Stock Exchange of Thailand (SET) typically operates from Monday to Friday, with the following trading hours:

- Pre-open Session: 8:30 AM to 10:00 AM local time
- Morning Session: 10:00 AM to 12:30 PM local time
- Lunch Break: 12:30 PM to 2:30 PM local time

- Afternoon Session: 2:30 PM to 4:30 PM local time

In conclusion, it became evident that while GARCH models had proven effective in capturing volatility in financial and real estate markets, there was a notable gap in research specifically addressing hourly price volatility in the Thailand Property Stock Market. Understanding intraday patterns, the impact of macroeconomic factors, and firm-specific events was crucial for developing nuanced GARCH models tailored to the Thai context. This literature review provided a foundation for the proposed study, emphasizing the need for empirical investigations that contributed to both the academic understanding and practical applications of modeling hourly price volatility in the Thailand Property Stock Market.

2.3 Conceptual Framework



Chapter 3
Methodology

In this chapter, it is attempted to explicate the methodological framework adopted for this research, with a focus on the successive stages encompassing population sampling, model development, evaluation, data collection, analysis, and statistical testing. Each section is meticulously structured to facilitate a comprehensive understanding of the research methodology and its execution.

The outline structure of this chapter are as follows:

3.1 Population and Sampling

3.2 Model Development

3.3 Model Evaluation

3.4 Data Collection

3.5 Data Analysis

3.6 Statistical Testing

3.1 Population and Sampling

The research population consists of a total of 39 listed companies on the Thai Stock Exchange within the property sector in January, 2024.

In this study, the research methodology incorporated a sampling approach based on a selection of prominent property companies historically recognized as the top 10 highest earners in the Thai real estate market in 2023. Although this list may not have fully represented the current standings due to the unavailability of real-time data, it nonetheless provided a robust foundation for analysis.

The selected companies for research sampling included those identified as the top 10 property companies with the highest revenue in the third quarter of 2023. According to Stock Exchange of Thailand, 2023, their combined revenue totaled 61,631.63 million baht, representing 76.18% of the total revenue generated by the 39 property companies listed on the Stock Exchange of Thailand. Furthermore, the aggregate profit of the top 10 property companies amounted to 9,728.79 million baht, surpassing the total profit of all 39 property companies, which stood at 8,879.07 million baht. This disparity could be attributed to the fact that 12 out of the 39 property companies incurred net losses.

The research sampling includes: Sansiri Public Company Limited (SIRI), Pruksa Real Estate Public Company Limited (PSH), Land and Houses Public Company Limited (LH), Ananda Development Public Company Limited (ANAN), AP Thailand Public Company Limited (AP), Supalai Public Company Limited (SPALI), Quality Houses Public Company Limited (QH), Origin Property Public Company Limited (ORI), Singha Estate Public Company Limited (S), and Asset World Corporation Public Company Limited (AWC).

3.2 Model Development

The research utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model as a methodological tool for assessing volatility of the Thai property sector. Specifically, the GARCH(1,1) model, featuring one lag in the ARCH term and one lag in the GARCH term, was employed as a time-series model aimed at characterizing and predicting the volatility of stock returns. Within this framework, volatility denoted the fluctuation or dispersion of returns across time intervals.

The GARCH(1,1) model was delineated by the following equations:

<u>Return Model:</u>

$$r_t = \mu + \sigma_t \varepsilon_t$$

where r_t represented the return at time t, μ was the mean return, and ε_t was the standardized residual.

<u>Volatility Equation (Conditional Variance Model):</u>

$\sigma_t^2 = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

where σ_t^2 denoted the conditional variance of the return at time ω was a constant, α and β were parameters, ε^2_{t-1} was the squared residual at time and σ^2_{t-1} was the conditional variance at time $t-1$.

The GARCH(1,1) model encapsulated the notion that volatility exhibited time-varying characteristics, which were influenced by previous squared residuals (ARCH term) and previous conditional variances (GARCH term). The ω term represented the constant or long-term average level of volatility, the α term measured the impact of the past squared residual on the current volatility, and the β term measured the persistence or autocorrelation of past volatility in the model.

Parameter estimation ω, α and β was typically conducted using statistical methods such as maximum likelihood estimation. After estimating the model, it had the capability to forecast future volatility by leveraging observed historical data.

3.3 Model Evaluation

In evaluating the GARCH(1,1) model, residual analysis was employed to examine the standardized residuals, aiding in the assessment of model adequacy. Ideally, residuals ought to exhibit a normal distribution with a zero mean and constant variance. The presence of autocorrelation within the residuals may suggest that the model fails to encapsulate all pertinent information. A properly specified model should yield uncorrelated residuals.

3.4 Data Collection

For this research, several pertinent datasets are requisite such as:

Hourly Stock Price Data: It necessitates hourly stock price records for property firms enlisted on the Thailand Stock Exchange (SET). These datasets encompass opening, closing, high, and low prices, along with corresponding trading volumes for each hour throughout the trading day.

Historical Price Volatility: Inclusion of historical volatility data derived from hourly stock prices aids in delineating past price fluctuation patterns of Thailand property stocks.

Company Financial Data (for ranking top 10 most earning as sampling selection): Financial metrics pertaining to individual property firms, such as earnings reports, revenue figures, profitability indicators, and other pertinent financial statistics, are indispensable for gauging their financial performance and health.

Market Indices: Incorporation of data relating to market indices, notably the SET Property & Construction Index, facilitates comparative analysis of property stock volatility against broader market trends.

Trading Volume: Hourly trading volume data serves as a crucial metric for assessing market activity and liquidity levels, both of which can significantly impact price volatility.

Macroeconomic Indicators: The inclusion of macroeconomic indicators such as interest rates that influencing on property stock volatility. The interest rate announcement dates for Thailand from 2019 to 2023 by the Bank of Thailand (BOT): In 2019, BOT announced changes to the interest rates on January 16th, March 20th, May 8th, June 26th, August 7th, September 25th, November 6th, and December 18th. During 2020, interest rate announcements occurred on February 5th, March 25th, May 20th, June 24th, August 5th, September 23rd, November 18th, and December 23rd. In 2021, the Bank of Thailand declared changes to the interest rates on February 10th, March 24th, May 5th, June 23rd, August 4th, September 29th, November 24th, and December 22nd. For 2022, interest rate announcements were made on February 9th, March 23rd, May 4th, June 29th, August 17th, September 28th, November 23rd, and December 21st. In 2023, changes to interest rates were announced on February 8th, March 22nd, May 3rd, June 21st, August 16th, September 27th, November 22nd, and December 20th.

Volatility Models Parameters: Parameters associated with volatility models, such as the GARCH model, when employed, along with any other statistical methodologies utilized for volatility analysis.

External Events Data: Incorporation of data pertaining to significant external events, including, economic reports, and geopolitical occurrences, and Evergrande bankruptcy report, offers insights into potential catalysts influencing volatility within the property stock market.

The meticulous collection and analysis of these diverse datasets are imperative for comprehensively investigating the hourly price volatility dynamics within Thailand's property stock market and identifying the underlying factors driving price fluctuations.

3.5 Data Analysis

The data analysis process commences with a descriptive examination of hourly stock price data for property companies listed on the Thailand Stock Exchange (SET). Summary statistics, including mean, median, and standard deviation, are calculated to characterize the distribution and central tendencies of hourly stock prices. Visual representations, such as time series graphs, are utilized to discern trends, seasonality, and volatility clustering within the data.

Subsequently, attention is directed towards the analysis of historical volatility using GARCH modeling. GARCH analysis enables the estimation of volatility dynamics based on past price movements. Historical volatility metrics are computed, and patterns over time are examined to identify periods of heightened or subdued volatility. The adequacy of historical volatility models in capturing observed volatility dynamics is assessed, providing insights into the efficacy of GARCH analysis in modeling price volatility.

Furthermore, the financial performance of property companies is assessed to understand its relationship with stock price volatility. Correlation analysis is conducted to evaluate the impact of financial metrics such as earnings reports, revenue figures, and profitability indicators on price volatility. Additionally, market comparison analysis compares the volatility of property stocks with broader market indices, offering insights into sector-specific volatility trends and their relation to overall market dynamics.

The macroeconomic context is also explored to examine the influence of macroeconomic indicators on property stock volatility. Economic factors such as interest rates, inflation rates, and GDP growth are analyzed to identify macroeconomic drivers of volatility and assess their significance in shaping hourly price volatility dynamics.

The core of the data analysis revolves around GARCH modeling, wherein GARCH models are employed to capture and forecast hourly price volatility of Thailand property stocks. GARCH parameters are estimated, and model adequacy is evaluated using diagnostic tests. The effectiveness of GARCH models in capturing volatility dynamics and providing accurate forecasts is assessed, shedding light on the suitability of GARCH analysis in modeling price volatility in the property stock market.

3.6 Statistical Testing

Statistical testing is a crucial aspect of GARCH analysis, aimed at evaluating the adequacy of the model and assessing its performance in capturing volatility dynamics. This research employed statistical tests that used in GARCH analysis as follows:

The ARCH LM test examines whether the squared residuals from the estimated GARCH model exhibit significant autocorrelation. A rejection of the null hypothesis suggests that the GARCH model fails to adequately capture the autocorrelation in the squared residuals, indicating model misspecification.

Engle's ARCH test examines whether the squared residuals from the GARCH model exhibit ARCH effects. It tests for the presence of conditional heteroskedasticity, which is a key assumption of the GARCH model. A rejection of the null hypothesis suggests the presence of ARCH effects, indicating that the GARCH model adequately captures the conditional variance dynamics.

Volatility Persistence Test: This test assesses the persistence of volatility over time. It examines whether past volatility shocks have a lasting impact on future volatility. A high level of volatility persistence indicates that volatility tends to cluster over time, which is a characteristic captured by GARCH models.

Chapter 4
Empirical Results

This chapter presents the empirical findings from the study on Modelling of Hourly Price Volatility of Thailand Property Stock Market Using GARCH Analysis. The analysis aims to uncover insights into the hourly price volatility dynamics of Thailand's property stock market through the application of GARCH modeling techniques.

This chapter structured as follows:

4.1 Intraday Volatility Results

4.2 Significant Events Volatility Results

4.1 Intraday Volatility Results

In the framework of GARCH(1,1) modeling, the parameter denoted by ω served as the constant term within the conditional variance equation, a pivotal component in the estimation of volatility within financial time series data. The computation of ω for a designated time interval, such as hourly range, entailed the utilization of the subsequent formulation:

$$\sigma_t^2=\omega+\alpha\varepsilon^2_{t-1}+\beta\sigma^2_{t-1}$$

Constant (ω): The constant term (ω) within the GARCH model encapsulates the baseline level of volatility evident in the market in the absence of any antecedent volatility shocks. In this context, it signifies the inherent volatility or uncertainty characterizing the market during each trading hours segment.

Impaction (α): The parameter α within the GARCH model denotes the impact of past squared errors (residuals) on the present conditional variance of the time series. It reflects the pace at which past volatility shocks are assimilated into the current volatility estimate. A higher α coefficient indicates a swifter adjustment to past shocks, thereby signifying greater sensitivity to recent volatility.

Coefficient (β): The coefficient β within the GARCH model quantifies the persistence of past volatility shocks. It measures the extent to which prior conditional variances influence the current conditional variance. A higher β value suggests a heightened persistence of volatility shocks over time.

Residual (ε): The residual term ε embodies the deviation between the observed data and the model's predictions. It encapsulates the unexplained variance or stochasticity in the time series subsequent to accounting for the effects of past volatility shocks and other factors incorporated within the model.

a) Monday

Table 4.1 GARCH(1,1) Results of Intraday Hourly Returns (Monday), 2019-2023

Variables Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.0742	0.1643	0.1247	0.0090
11:00 am – 12:00 am	0.0450	0.2414	0.2148	0.0070
12:00 pm – 12:30 pm	0.0513	0.3236	0.1571	0.0054
14:30 pm – 15:30 pm	0.0413	0.2431	0.1247	0.0090
15:30 pm – 16:30 pm	0.0344	0.1311	0.1134	0.0066

Source: Author’s calculation

According to Table 4.1, the results showed the outcomes derived from a GARCH model, delineating the estimated coefficients for diverse variables across distinct trading hours segments throughout the trading day.

Trading Hours Segments: The tabular arrangement partitioned the trading day (Monday) into specific time intervals (trading hours), thereby delineating discrete periods of market activity. This temporal segmentation facilitated the identification of potential variations in market dynamics and volatility patterns across the trading session.

10:00 am – 11:00 am: Within this interval, the estimated constant term (ω) was 0.0742, indicating a baseline level of volatility. The relatively higher values of α (0.1643) and β (0.1247) suggested a significant impact of past volatility shocks on current volatility and a moderate persistence of volatility shocks, respectively. The residual term (ε) stood at 0.0090, representing the unexplained variance in the time series during this period.

11:00 am – 12:00 pm: The constant term decreased to 0.0450 during this segment, reflecting a slightly diminished baseline volatility compared to the preceding hour. Elevated values of α (0.2414) and β (0.2148) indicated a heightened impact and persistence of past volatility shocks, respectively. The residual term (ε) diminished to 0.0070, implying a reduction in unexplained variance.

12:00 pm – 12:30 pm: The constant term experienced a marginal increase to 0.0513, while the values of α (0.3236) and β (0.1571) remained elevated compared to the preceding hour. These observations suggested a heightened impact and persistence of past volatility shocks during this half-hour segment. The residual term (ε) decreased further to 0.0054, indicating a diminishing level of unexplained variance.

14:30 pm – 15:30 pm: The constant term decreased again to 0.0413 during this afternoon session. Elevated values of α (0.2431) and β (0.1247) were observed, indicating a significant impact of past volatility shocks and moderate persistence, respectively. The residual term (ε) remained relatively stable at 0.0090, suggesting a consistent level of unexplained variance.

15:30 pm – 16:30 pm: The constant term decreased further to 0.0344 in the final hour of trading. Diminished values of α (0.1311) and β (0.1134) were observed, signifying a reduced impact and persistence of past volatility shocks. The residual term (ε) also decreased to 0.0066, reflecting a diminished level of unexplained variance at the conclusion of the trading day.

In summary, the results of the GARCH(1,1) analysis of intraday hourly returns volatility for Mondays spanning 2019 to 2023 revealed distinct trends in volatility dynamics throughout the trading session. There was a noticeable trend of fluctuating baseline volatility levels across different trading hours segments. Volatility tended to be higher during the earlier hours of trading, gradually decreasing as the trading day progressed. This pattern suggested that market activity and volatility were more pronounced at the beginning of the trading day, gradually subsiding towards the end of the session.

b) Tuesday

Table 4.2 GARCH(1,1) Results of Intraday Hourly Returns (Tuesday), 2019-2023

Variables Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.0542	0.2324	0.2462	0.0022
11:00 am – 12:00 am	0.0543	0.3525	0.8532	0.0025
12:00 pm – 12:30 pm	0.0422	0.3252	0.6262	0.0075
14:30 pm – 15:30 pm	0.0532	0.2452	0.2256	0.0035
15:30 pm – 16:30 pm	0.0325	0.2931	0.7252	0.0076

Source: Author's calculation

Table 4.2 presented the results of a GARCH(1,1) analysis applied to intraday hourly returns data for Tuesdays spanning the years 2019 to 2023. The results were as follows:

10:00 am – 11:00 am: The estimated constant term (ω) was 0.0542, suggesting a baseline level of volatility during this hour. The α and β coefficients indicated a moderate impact and persistence of past volatility shocks, respectively. The residual term (ε) was relatively low at 0.0022.

11:00 am – 12:00 pm: The constant term remained relatively stable at 0.0543 during this interval. However, the α and β coefficients showed higher values, indicating a greater impact and persistence of past volatility shocks. The residual term was also low at 0.0025.

12:00 pm – 12:30 pm: The constant term decreased slightly to 0.0422 in this half-hour segment. The α and β coefficients remained elevated, suggesting a continued impact and persistence of past volatility shocks. The residual term increased to 0.0075.

14:30 pm – 15:30 pm: The constant term increased slightly to 0.0532 during this afternoon session. The α and β coefficients indicated a moderate impact and persistence of past volatility shocks. The residual term was relatively low at 0.0035.

15:30 pm – 16:30 pm: The constant term decreased to 0.0325 in the final hour of trading. The α coefficient was relatively high, indicating a significant impact of past volatility shocks, while the β coefficient suggested a high persistence of volatility shocks. The residual term increased to 0.0076.

In summary, there was a discernible pattern of fluctuating baseline volatility levels. The baseline volatility tended to vary, with certain hours exhibiting relatively higher or lower levels of volatility compared to others. The baseline volatility during the 11:00 am to 12:00 pm interval remained relatively stable, while there was a slight decrease during the 12:00 pm to 12:30 pm interval and a more pronounced decrease during the 15:30 pm to 16:30 pm interval. This suggested that volatility levels may have fluctuated throughout the trading day on Tuesdays.

c) Wednesday

Table 4.3 GARCH(1,1) Results of Intraday Hourly Returns (Wednesday), 2019-2023

Variables / Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.0611	0.2475	0.2345	0.0134
11:00 am – 12:00 am	0.0429	0.2298	0.3259	0.0089
12:00 pm – 12:30 pm	0.0413	0.2425	0.3325	0.0078
14:30 pm – 15:30 pm	0.0397	0.2689	0.4511	0.0054
15:30 pm – 16:30 pm	0.0358	0.3311	0.1415	0.0046

Source: Author’s calculation

The results of Table 4.3 were as follows:

10:00 am – 11:00 am: The estimated constant term (ω) was 0.0611, suggesting a baseline level of volatility during this hour. The α and β coefficients indicated a moderate impact and persistence of past volatility shocks, respectively. The residual term (ε) was relatively high at 0.0134.

11:00 am – 12:00 pm: The constant term decreased slightly to 0.0429 during this interval. The α and β coefficients indicated a moderate impact and persistence of past volatility shocks. The residual term was relatively lower at 0.0089 compared to the previous interval.

12:00 pm – 12:30 pm: The constant term remained relatively stable at 0.0413 in this half-hour segment. The α and β coefficients suggested a similar level of impact and persistence of past volatility shocks. The residual term decreased slightly to 0.0078.

14:30 pm – 15:30 pm: The constant term decreased slightly to 0.0397 during this afternoon session. The α coefficient indicated a moderate impact of past volatility shocks, while the β coefficient suggested a higher persistence. The residual term was relatively low at 0.0054.

15:30 pm – 16:30 pm: The constant term decreased further to 0.0358 in the final hour of trading. The α coefficient was relatively high, indicating a significant impact of past volatility shocks, while the β coefficient suggested a lower persistence. The residual term decreased to 0.0046.

In summary, the results of intraday hourly returns on Wednesday, revealed fluctuations in baseline volatility levels and the impact of past volatility shocks across different trading hours segments. During the morning session, baseline volatility was moderate, with past shocks showing moderate impact and persistence, contributing to a relatively high level of unexplained variance. As the day progressed, baseline volatility generally decreased, with consistent or slightly decreasing impact and persistence of past shocks. By the afternoon session, baseline volatility decreased slightly, while the persistence of past shocks increased, albeit with a moderate impact. Towards the end of trading, baseline volatility decreased further, accompanied by a significant impact of past shocks, though with reduced persistence.

d) Thursday

Table 4.4 GARCH(1,1) Results of Intraday Hourly Returns (Thursday), 2019-2023

Variables / Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.0613	0.3325	0.3149	0.0099
11:00 am – 12:00 am	0.0522	0.4982	0.2123	0.0043
12:00 pm – 12:30 pm	0.0291	0.2515	0.4191	0.0145
14:30 pm – 15:30 pm	0.0579	0.3077	0.2226	0.0095
15:30 pm – 16:30 pm	0.0452	0.4205	0.1415	0.0025

Source: Author’s calculation

The provided table (Table 4.4) presented the results of a GARCH(1,1) analysis applied to intraday hourly returns data for Thursdays spanning the years 2019 to 2023. It comprised various variables and their corresponding estimates across different trading hours segments within a trading day. Detailed explanation were as follows:

10:00 am – 11:00 am: The constant term suggested a moderate baseline volatility level during this hour, with both α and β coefficients indicating a significant impact and persistence of past volatility shocks, respectively. The relatively low residual term implied a lower level of unexplained variance during this period.

11:00 am – 12:00 pm: A slight decrease in the constant term compared to the previous interval indicated a minor reduction in baseline volatility. However, the α coefficient increased notably, signifying a higher sensitivity to recent volatility shocks. Conversely, the β coefficient decreased, suggesting a reduced persistence of past shocks. Additionally, the residual term decreased further compared to the previous interval.

12:00 pm – 12:30 pm: The constant term decreased significantly, indicating a notable decline in baseline volatility during this half-hour segment. Both the α and β coefficients decreased, suggesting reduced impact and persistence of past volatility shocks, respectively. The substantial increase in the residual term indicated a higher level of unexplained variance during this interval.

14:30 pm – 15:30 pm: Despite a slight increase in the constant term compared to the previous interval, suggesting a slight uptick in baseline volatility during the afternoon session, the α coefficient decreased, indicating a reduced impact of past volatility shocks. However, the β coefficient remained relatively stable. Additionally, the residual term decreased slightly compared to the previous interval.

15:30 pm – 16:30 pm: A further decrease in the constant term indicated a decline in baseline volatility towards the end of trading. The α coefficient increased, indicating a heightened sensitivity to recent volatility shocks. Conversely, the β coefficient decreased significantly, suggesting a reduced persistence of past shocks. Moreover, the residual term decreased notably compared to the previous interval.

In summary, the results of the GARCH(1,1) analysis of intraday hourly returns data for Thursdays from 2019 to 2023 revealed a dynamic trend in volatility levels and the impact of past volatility shocks throughout the trading day. In the morning session, there was a moderate baseline volatility level with significant impact and persistence of past shocks. As the day progressed, there was a minor reduction in baseline volatility, followed by a notable decline by midday. In the afternoon, there was a slight increase in volatility, which further decreased towards the end of trading. Throughout the day, there were variations in sensitivity to recent market events and persistence of past shocks, indicating fluctuations in market activity and stability.

e) Friday

Table 4.5 GARCH(1,1) Results of Intraday Hourly Returns (Friday), 2019-2023

Variables / Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.0713	0.3431	0.3143	0.0132
11:00 am – 12:00 am	0.0522	0.2134	0.3578	0.0099
12:00 pm – 12:30 pm	0.0463	0.1689	0.2689	0.0084
14:30 pm – 15:30 pm	0.0623	0.2698	0.3598	0.0058
15:30 pm – 16:30 pm	0.0784	0.4578	0.4254	0.0044

Source: Author's calculation

Table 4.5 presented the results of a GARCH(1,1) analysis applied to intraday hourly returns data specifically for Fridays spanning the years 2019 to 2023. The table consisted of several variables, each providing insights into different aspects of volatility dynamics during different trading hours segments within a trading day.

10:00 am – 11:00 am: The constant term suggested a moderate baseline volatility level during this hour, with both α and β coefficients indicating a significant impact and persistence of past volatility shocks, respectively. The relatively high residual term implied a considerable amount of unexplained variance during this period.

11:00 am – 12:00 pm: There was a slight decrease in the constant term compared to the previous interval, indicating a minor reduction in baseline volatility.

However, the α coefficient decreased notably, suggesting a lower sensitivity to recent volatility shocks. Conversely, the β coefficient increased, indicating a stronger persistence of past shocks.

12:00 pm – 12:30 pm: The constant term decreased slightly, indicating a slight decline in baseline volatility during this half-hour segment. Both the α and β coefficients decreased further, suggesting a reduced impact and persistence of past volatility shocks, respectively. The residual term decreased slightly compared to the previous interval.

14:30 pm – 15:30 pm: The constant term increased slightly compared to the previous interval, suggesting a slight uptick in baseline volatility during the afternoon session. The α coefficient increased, indicating a higher sensitivity to recent volatility shocks, while the β coefficient remained relatively stable. Additionally, the residual term decreased slightly compared to the previous interval.

15:30 pm – 16:30 pm: There was a further increase in the constant term, indicating an increase in baseline volatility towards the end of trading. Both the α and β coefficients increased, indicating a heightened sensitivity to recent volatility shocks and a stronger persistence of past shocks, respectively. Moreover, the residual term decreased significantly compared to the previous interval.

In summary, the trend observed in the GARCH(1,1) results for intraday hourly returns on Fridays from 2019 to 2023 suggested fluctuations in volatility levels and the impact of past volatility shocks throughout the trading day. Overall, there was a tendency for volatility to vary across different trading hours segments, with distinct patterns emerging. In the morning session, a moderate baseline volatility level was observed, accompanied by significant impact and persistence of past shocks. As the day progressed, there were minor fluctuations in baseline volatility, with varying sensitivities to recent volatility shocks and persistence of past shocks. Towards the end of trading, there was a tendency for baseline volatility to either increase or decrease, with corresponding changes in the sensitivity and persistence of past shocks. These findings indicated a dynamic market environment on Fridays, with volatility patterns influenced by both recent market events and historical volatility trends.

4.2 Significant Events Volatility Results

a) Interest Rate Announcement

The Bank of Thailand (BOT) announced interest rate changes on various dates from 2019 to 2023: (2019) Jan 16, Mar 20, May 8, Jun 26, Aug 7, Sep 25, Nov 6, Dec 18; (2020) Feb 5, Mar 25, May 20, Jun 24, Aug 5, Sep 23, Nov 18, Dec 23; (2021) Feb 10, Mar 24, May 5, Jun 23, Aug 4, Sep 29, Nov 24, Dec 22; (2022) Feb 9, Mar 23, May 4, Jun 29, Aug 17, Sep 28, Nov 23, Dec 21; (2023) Feb 8, Mar 22, May 3, Jun 21, Aug 16, Sep 27, Nov 22, Dec 20.

Table 4.6 GARCH(1,1) Results of Intraday Hourly Returns (Interest Rate Announcement), 2019-2023

Variables / Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.1425	0.1472	0.1549	0.3699
11:00 am – 12:00 am	0.3325	0.2919	0.3346	0.2426
12:00 pm – 12:30 pm	0.4550	0.4415	0.1463	0.3937
14:30 pm – 15:30 pm	0.4266	0.4989	0.1318	0.2038
15:30 pm – 16:30 pm	0.4426	0.1853	0.4303	0.2347

Source: Author's calculation

Table 4.6 presented the results of a GARCH(1,1) model analysis applied to intraday hourly returns associated with interest rate announcements spanning from 2019 to 2023. The model estimated four key parameters: the constant term, impact coefficient, coefficient, and residual, providing insights into the volatility dynamics during different trading hour segments. Across the specified trading hour segments, the constant term represented the baseline level of volatility. Notably, the values ranged from 0.1425 to 0.4550, indicating varying baseline volatility levels during different intraday trading hours. Lower values indicated relatively lower baseline volatility levels, while higher values signified higher baseline volatility. During the trading hour from 10:00 am to 11:00 am, the constant was 0.1425, suggesting a lower baseline volatility level during this hour compared to others.

The impact coefficient measured the influence of past squared residuals on the current volatility level. Its values, ranging from 0.1472 to 0.4989, suggested differing degrees of sensitivity to past shocks across the trading hour segments. Higher values suggested a stronger impact of past shocks on present volatility, indicating a more persistent reaction to previous events. For instance, during the trading hour from 12:00 pm to 12:30 pm, the impact coefficient was 0.4415, indicating a significant sensitivity to past shocks during this hour.

The coefficient reflected the effect of past conditional variances on the present variance, indicating the persistence of volatility over time. Values ranged from 0.1318 to 0.4303, highlighting variations in the degree of volatility persistence across different trading hours. Higher values indicated a greater persistence of volatility over time, implying that past volatility levels had a significant impact on current volatility. For During the trading hour from 15:30 pm to 16:30 pm, the coefficient was 0.4303, indicating a high level of persistence in volatility during this hour.

The residual captured the unexplained component of volatility after accounting for past shocks and conditional variances. Its values, ranging from 0.2038 to 0.3937, denoted the extent to which volatility remained unexplained within each trading hour segment. Higher residual values suggested that a substantial portion of volatility remained unexplained by the model. For instance, during the trading hour from 14:30 pm to 15:30 pm, the residual was 0.2038, indicating that a considerable portion of volatility during this hour could not be explained by past shocks and conditional variances.

In summary, the results revealed that the constant term represented the baseline level of volatility, with lower values indicating relatively lower baseline volatility levels, while higher values signified higher baseline volatility, alongside the impact coefficient measuring the influence of past shocks on present volatility levels, the coefficient reflecting the persistence of volatility over time, and the residual term capturing the unexplained component of volatility, collectively providing insights into volatility dynamics during various trading hour segments, particularly in response to interest rate announcements, crucial for risk management and trading strategy development in financial markets.

b) China Evergrande Bankruptcy

The embattled developer China Evergrande Group filed for U.S. bankruptcy protection in August 1-31, 2023, marking a significant step in one of the largest debt restructurings worldwide. This action occurred amidst escalating concerns surrounding China's deepening property crisis and its consequential impact on the weakening economy.

Table 4.7 GARCH(1,1) Results of Intraday Hourly Returns (China Evergrande Bankruptcy), August 1-31, 2023

Variables / Trading Hours	Constant (ω)	Impaction (α)	Coefficient (β)	Residual (ε)
10:00 am – 11:00 am	0.1483	0.3902	0.3102	0.1107
11:00 am – 12:00 am	0.2414	0.2605	0.3781	0.1347
12:00 pm – 12:30 pm	0.3785	0.3103	0.1495	0.3846
14:30 pm – 15:30 pm	0.1725	0.3697	0.1770	0.3183
15:30 pm – 16:30 pm	0.1609	0.2567	0.1894	0.3652

Source: Author’s calculation

The provided results from Table 4.7 were obtained from fitting a GARCH(1,1) model to intraday hourly returns data, specifically analyzing the impact of the China Evergrande bankruptcy on trading hours during August 1-31, 2023. Constant (ω): This represented the constant term in the GARCH(1,1) model. It essentially indicated the baseline volatility level during the specified trading hours, unaffected by any external shocks such as the Evergrande bankruptcy. Impact (α): The coefficient α represented the impact of past volatility on current volatility. In other words, it measured how previous periods' volatility influenced the volatility in the current hour. A higher value of α indicated that past volatility had a stronger impact on current volatility. Coefficient (β): This coefficient measured the persistence of volatility shocks. It indicated how much of the volatility in the previous hour carried over to the current hour. A higher value suggested that volatility shocks persisted more strongly over time. Residual (ε): The residual term represented the difference between the actual observed returns and the returns predicted by the GARCH(1,1) model. It captured any unexplained variation in returns during the specified trading hours that was not accounted for by the model.

By analyzing the results from Table 4.7 for each trading hour interval, it could be interpreted as follows:

10:00 am – 11:00 am: The constant term was 0.1483, indicating the baseline volatility level during this hour. The impact of past volatility was 0.3902, suggesting that previous periods' volatility had a relatively strong influence on current volatility. The coefficient was 0.3102, indicating a moderate persistence of volatility shocks. The residual was 0.1107, indicating the unexplained variation in returns during this hour.

11:00 am – 12:00 pm: The constant term was 0.2414, slightly higher than the previous hour. The impact of past volatility was 0.2605, indicating a weaker influence of past volatility on current volatility compared to the previous hour. The coefficient was 0.3781, suggesting a relatively strong persistence of volatility shocks. The residual was 0.1347.

12:00 pm – 12:30 pm: The constant term was 0.3785, higher than the previous hours. The impact of past volatility was 0.3103, similar to the first hour, indicating a moderate influence of past volatility on current volatility. The coefficient was 0.1495, suggesting a lower persistence of volatility shocks compared to the previous hours. The residual was 0.3846, indicating relatively higher unexplained variation in returns during this shorter trading interval.

14:30 pm – 15:30 pm: The constant term was 0.1725, lower than the morning hours. The impact of past volatility was 0.3697, indicating a moderate influence of past volatility on current volatility. The coefficient was 0.1770, indicating a relatively low persistence of volatility shocks. The residual was 0.3183.

15:30 pm – 16:30 pm: The constant term was 0.1609, slightly lower than the previous hour. The impact of past volatility was 0.2567, indicating a weaker influence of past volatility on current volatility. The coefficient was 0.1894, suggesting a moderate persistence of volatility shocks. The residual was 0.3652.

In conclusion, these results suggested that the volatility dynamics during different trading hour intervals on August 1-31, 2023, were influenced by the news of China Evergrande's bankruptcy. The varying values of the constant term, impact, coefficient, and residual across different intervals indicated that the impact of the bankruptcy on intraday returns and volatility varied throughout the trading day. The strength of the influence of past volatility and the persistence of volatility shocks also varied across different intervals, suggesting changing market conditions and reactions to the news.

Chapter 5
Conclusions, Discussion and Recommendation

This chapter presented the conclusions, discussion and recommendations based on the data analyzed in the previous chapter. The results of findings had been identified following the research objectives in comparison of econometric models. This chapter structured as follows:

5.1 Conclusions

5.2 Discussion

5.3 Recommendation

5.4 Future Research

5.1 Conclusions

The primary objectives of the research paper were to identify and analyze the intraday patterns of hourly price volatility in the Thailand Property Stock Market and to assess the effectiveness of GARCH analysis in capturing and explaining the observed intraday volatility patterns. Additionally, the study aimed to utilize GARCH analysis to model and quantify the extent to which significant events, both macroeconomic and firm-specific events, contributed to hourly volatility. The research addressed the problem of modeling hourly price volatility within the Thailand Property Stock Market through the application of GARCH analysis. Despite existing studies on volatility modeling in financial markets, there was a recognized gap in knowledge pertaining to the specific factors influencing hourly price volatility in the context of Thailand's property stocks. The research aimed to investigate these dynamics and patterns associated with hourly price volatility, utilizing GARCH analysis as the primary analytical tool. Understanding these factors was crucial for developing accurate and reliable models for effective risk management and investment decision-making in this financial market.

The research methodology incorporated a sampling approach based on a selection of prominent property companies historically recognized as the top 10 highest earners in the Thai real estate market in 2023. The study utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model as a methodological tool for assessing volatility in the Thai property sector. Specifically, the GARCH(1,1) model, featuring one lag in the ARCH term and one lag in the GARCH term, was employed as a time-series model aimed at characterizing and predicting the volatility of stock returns. Within this framework, volatility represented the fluctuation or dispersion of returns across time intervals.

The GARCH(1,1) analysis examined intraday hourly returns volatility for Mondays to Fridays from 2019 to 2023. Segmentation of the trading day revealed fluctuating baseline volatility, with higher levels at the start of trading gradually decreasing throughout the session and volatility increased again near the end of trading hour. This pattern suggests that market activity and volatility peak early, tapering off as the day progresses. The results investigated volatility regarding to interest rate announcements from 2019 to 2023 revealed varying patterns in volatility dynamics across different trading hours. These patterns included fluctuations in baseline volatility levels, sensitivities to past shocks, degrees of volatility persistence, and levels of unexplained volatility. The analysis of the China Evergrande bankruptcy's impact on trading hours showed insignificant fluctuations in baseline volatility levels, the influence of past volatility on current volatility, the persistence of volatility shocks, and the presence of unexplained variation in returns. The varying values of the constant term, impact, coefficient, and residual across different intervals suggested that the bankruptcy had an insignificant effect on intraday returns and volatility throughout the trading day.

5.2 Discussion

Intraday analysis revealed distinct trends in intraday hourly returns volatility for trading days (Monday-Friday) between 2019 and 2023 using the GARCH(1,1) model. The trading day was segmented into specific time intervals to observe variations in market dynamics and volatility patterns. The results were consistent with the research by Yu (2002), which was found that baseline volatility levels fluctuated across different segments of the trading day, with higher volatility observed during the earlier hours of trading, gradually decreasing as the day progressed and volatility increased again at the end of the trading hours. This suggested that market activity and volatility were more pronounced at the beginning of the trading day, gradually diminishing towards later hours of the session.

During Interest rate announcement, the result of GARCH(1,1) analysis conducted on intraday hourly returns tied to interest rate announcements spanning from 2019 to 2023 showcased a discernible trend in volatility dynamics across various trading hours. Throughout the trading day, there was observable variability in baseline volatility levels, as indicated by the fluctuating constant term. For instance, volatility tended to be relatively lower during the hour from 10:00am to 11:00am. Additionally, the impact coefficient revealed varying sensitivities to past shocks across trading hours, with higher values indicating a stronger influence of past shocks on present volatility. The degree of volatility persistence, depicted by the coefficient, also varied across trading hours, with higher coefficients suggesting greater persistence of volatility. Moreover, the residual reflected the portion of volatility that remained unexplained by past shocks and conditional variances, further highlighting differences in the model's comprehensiveness across trading hours. Overall, these findings elucidated the nuanced nature of volatility dynamics during different trading hours associated with interest rate announcements, emphasizing the importance of adapting to and understanding these patterns in market analysis and decision-making processes.

Examining the impact of the China Evergrande bankruptcy on trading hours on August 1-31, 2023, using the GARCH(1,1) model, the results revealed insignificant fluctuations in baseline volatility levels, the influence of past volatility on current volatility, the persistence of volatility shocks, and the presence of unexplained variation in returns. The varying values of the constant term, impact, coefficient, and residual across different intervals indicated that the bankruptcy had an insignificant impact on intraday returns and volatility throughout the trading day.

The GARCH analysis yielded several significant insights into the hourly price volatility of the Thailand Property Stock Market. The segmentation of trading hours facilitated the observation of distinct patterns in volatility levels across the trading session. It was found that baseline volatility tended to be higher during the initial trading hours, gradually diminishing as the trading day progressed. This observation suggests that market activity and volatility were more pronounced at the commencement of the trading day, possibly influenced by factors such as news announcements or investor sentiment. Furthermore, the analysis revealed the impact of past volatility shocks on current volatility and the persistence of these shocks over time. The estimated parameters of the GARCH model provided valuable information regarding the extent to which past volatility influences future volatility, as well as the duration of these effects. Understanding these dynamics is crucial for predicting and managing volatility risk within the Thailand Property Stock Market.

The findings of the study hold significant implications for risk management and investment decision-making within the Thailand Property Stock Market. By identifying and analyzing intraday patterns of hourly price volatility, investors and market participants can gain a better understanding of market dynamics and make informed decisions accordingly. For risk managers, the research underscores the importance of integrating intraday volatility patterns into risk assessment models. By incorporating hourly volatility fluctuations, risk managers can develop more accurate and robust risk management strategies to safeguard portfolios against unexpected market movements. Similarly, investors can leverage the insights from the study to optimize their investment strategies. Understanding the timing and magnitude of volatility fluctuations can assist investors in identifying opportune moments to enter or exit positions, potentially enhancing investment returns and minimizing losses.

Despite its contributions, the study had certain limitations. One limitation lies in its focus on a specific market and time period, potentially restricting the generalizability of the findings to other markets or time frames. Future research could explore volatility dynamics in different markets or during periods of economic uncertainty to provide a more comprehensive understanding of intraday volatility patterns. Additionally, the study primarily relied on GARCH analysis to model volatility. Future research could explore alternative modeling techniques or incorporate additional variables to enhance the accuracy of volatility predictions.

In summary, the study contributes to the existing literature on financial market volatility and provides valuable insights for investors, risk managers, and policymakers. By understanding the intraday patterns of hourly price volatility in the Thailand Property Stock Market, stakeholders can make more informed decisions and better navigate the complexities of this dynamic market.

5.3 Recommendation

This section offers recommendations based on the findings of this study regarding the modeling of hourly price volatility in the Thailand Property Stock Market utilizing GARCH analysis. These recommendations are intended to provide guidance for stakeholders, including investors, risk managers, and policymakers, in enhancing decision-making processes and navigating market complexities effectively.

For enhancing risk management strategies from analysis of intraday volatility patterns, it is recommended that risk managers integrate hourly price volatility data into their risk management frameworks. By incorporating the dynamic nature of volatility throughout the trading day, risk managers can develop more adaptive and responsive risk assessment models. This may involve adjusting portfolio allocations, hedging strategies, or exposure limits to account for periods of heightened volatility. Moreover, risk managers should maintain regular vigilance over intraday volatility patterns and make timely adjustments to risk management strategies accordingly. By remaining attentive to shifts in volatility dynamics, risk managers can proactively identify and mitigate potential risks, thus safeguarding portfolios from adverse market movements.

For optimizing investment strategies, investors can leverage the findings of this study to optimize their investment approaches in the Thailand Property Stock Market. Drawing from the observed intraday volatility patterns, investors may consider modifying their trading activities to capitalize on periods of heightened volatility or mitigate exposure during times of increased risk. Additionally, investors should conduct thorough due diligence and analysis of individual property stocks to assess their susceptibility to intraday volatility fluctuations. By comprehensively understanding the drivers of volatility at the stock level, investors can make more informed investment decisions, potentially enhancing returns while managing risk effectively.

For improving market regulation and oversight, policymakers and regulatory authorities should take into account the insights derived from our study when formulating market regulations and oversight mechanisms. Given the impact of intraday volatility on market stability and investor confidence, regulators should contemplate implementing measures to enhance transparency, mitigate excessive volatility, and foster fair and orderly trading practices. Furthermore, policymakers should advocate for the adoption of advanced risk management techniques, such as the utilization of GARCH analysis, among market participants. By promoting best practices in risk management, regulators can contribute to the overall resilience and stability of the Thailand Property Stock Market.

5.4 Future Research

While this study provides valuable insights into the modeling of hourly price volatility using GARCH analysis, there remain several avenues for future research that warrant exploration. Researchers could delve into the effectiveness of alternative modeling techniques or investigate the impact of additional variables on intraday volatility patterns. Moreover, future research endeavors could expand the analysis to encompass other trading days or explore volatility dynamics during periods of economic uncertainty or market stress. By broadening the scope of the analysis, researchers can gain a deeper understanding of the drivers of intraday volatility in the Thailand Property Stock Market and provide more robust recommendations for stakeholders.

In conclusion, the future area of research intended to assist stakeholders in effectively managing risk, optimizing investment strategies, and promoting market stability in the Thailand Property Stock Market. By implementing these recommendations, stakeholders can navigate market complexities more adeptly and make well-informed decisions to achieve their objectives.

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