Information Asymmetry Transmissions between Futures and Spot Markets: Evidence from Thailand

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การส่งผ่านความไม่สมมาตรของข้อมูลระหว่างตลาดสัญญาซื้อขายล่วงหน้าและตลาดซื้อขายทันที-
หลักฐานจากประเทศไทย

น.ส.สุพิชญา พัฒนพานิชชัย

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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By	Miss Supichaya Pattanapanitchai
Field of Study	Finance
Thesis Advisor	Associate Professor ANIRUT PISEDTASALASAI, Ph.D.

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สุพิชญา พัฒนพานิชชัย : การส่งผ่านความไม่สมมาตรของข้อมูลระหว่างตลาดสัญญาซื้อขายล่วงหน้าและตลาดซื้อขายทันที-หลักฐานจากประเทศไทย. (Information Asymmetry Transmissions between Futures and Spot Markets: Evidence from Thailand) อ.ที่ปรึกษาหลัก : รศ. ดร.อนิรุต พิเสฏฐศลาศัย

การวิจัยนี้ศึกษาถึงความสัมพันธ์แบบนำ-ตาม ในด้านการไม่สมดุลของข้อมูลระหว่างตลาดเฟอร์เจอร์สและตลาดสปอตในประเทศไทย เราใช้ความผันผวนของความไม่สมดุลของคำสั่งซื้อ (VOIB) ในการระบุความไม่สมดุลนี้ โดยเน้นที่สามกลุ่มนักลงทุน: นักลงทุนต่างประเทศ (FI) สถาบันในประเทศ (LS) และนักลงทุนในประเทศ (LI) เราวิเคราะห์ข้อมูลจาก TFEX และ SET ในช่วงเวลาตั้งแต่เดือนมกราคม พ.ศ. 2560 ถึงธันวาคม พ.ศ. 2565 เพื่อหาแนวโน้มการซื้อขายของกลุ่มนักลงทุนเหล่านี้ ด้วยเทคนิคการวิเคราะห์แบบ vector autoregression (VAR) เราได้ทำการศึกษาความสัมพันธ์ระหว่างตัวแปรในตลาดเฟอร์เจอร์สและตลาดสปอต เรายังได้ประเมินผลกระทบจากการเกิดขึ้นทันทีหรือ 'shocks' ในตลาดหนึ่งๆ ต่อตลาดอื่นๆ โดยใช้ impulse response functions และ variance decomposition

ผลการค้นพบแสดงให้เห็นว่า นักลงทุนสถาบันและนักลงทุนในประเทศมีความสัมพันธ์กับการซื้อขายที่มีข้อมูลมากกว่านักลงทุนต่างประเทศ นักลงทุนในประเทศมักจะรับข้อมูลเร็วและแบ่งปันกับสถาบันในประเทศในตลาดสปอต นอกจากนี้แนวโน้มการซื้อขายในตลาดเฟอร์เจอร์สมีผลกระทบมากต่อตลาดหุ้น โดยเฉพาะในกลุ่มนักลงทุนสถาบันและนักลงทุนในประเทศ ซึ่งแสดงให้เห็นว่าข้อมูลสำคัญในตลาดเฟอร์เจอร์สถูกนำไปยังตลาดสปอตอย่างมีประสิทธิภาพ ผลการวิจัยนี้ยืนยันและสนับสนุนสมมติฐานของเราว่ามีนักลงทุนที่มีข้อมูลและนักลงทุนมักจะปรับเปลี่ยนการซื้อขายในตลาดเฟอร์เจอร์สก่อนที่จะทำการปรับเปลี่ยนในตลาดสปอต

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต	....
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Supichaya Pattanapanitchai : Information Asymmetry Transmissions between Futures and Spot Markets: Evidence from Thailand. Advisor: Assoc. Prof. ANIRUT PISEDTASALASAI, Ph.D.

This research investigates the existence of a lead-lag relationship in information asymmetry between Thailand's futures and spot markets. We use the volatility of order imbalance (VOIB) as an indicator of this asymmetry, concentrating on three investor groups: Foreign Investors (FI), Local Institutions (LS), and Local Investors (LI). Data from TFEX and SET, covering January 2017 to December 2022, was analyzed to identify trading patterns of these investor types. Using vector autoregression (VAR), we examined the connection between variables in the futures and spot markets. We also evaluated the impact of shocks in one market on the other using impulse response functions and variance decomposition.

Our findings showed that local institutional and local investors in Thailand are more linked with informed trading compared to foreign investors. Local investors often access information early and share it with local institutions in spot market. Furthermore, trading patterns in the futures market significantly influence those in the stock market, particularly among local institutional and local investors. This shows that key information in the futures market gets effectively transferred to the spot market. The findings of this study provided empirical support for our hypotheses, which implied the existence of informed traders who have information and investors tend to adjust their trading activities in the futures market prior to making adjustments in the spot markets

Field of Study: Finance		Student's Signature ....
Academic Year: 2023		Advisor's Signature ....

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Supichaya Pattanapanitchai

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1. Introduction

1.1 Background

Understanding the complex relationships between different types of financial markets is a significant component of financial economics. In Thailand, the daily trading volume increase by approximately 70% from 2017 to 2022 in the futures market, serves as a significant component of the country financial system. Conversely, the stock market saw an average daily trading increase of about 68% during the same period. The relationship between these two rapidly growing markets can offer insightful perspectives into market efficiency, price discovery, and market dynamics (Xiao et al, 2023). This study seeks to determine the origin and significance of the lead-lag relationship between trading activity in these two markets, a relationship that could have implications for a wide range of market participants, including investors, traders, and speculators (Ren et al, 2022).

Historically, financial literature indicates the existence of lead-lag relationships between futures and stock markets. For instance, in developed markets like the US, the futures market tends to lead the stock market. However, these lead-lag relationships may not express similarly in emerging markets due to differing market characteristics and stages of development (Li et al, 2022). Thailand represents a unique case in this context. Despite its status as an emerging market, it recorded a combined trading volume of futures and stock markets of nearly 2.5 trillion Thai Baht in 2022. While numerous studies have examined the lead-lag relationship in developed markets, relatively few have considered emerging markets such as Thailand, thus leaving a considerable gap in the existing literature (Ma et al, 2022).

This paper seeks to examine the lead-lag relation between trading activity between the futures and stock markets for various investor types. In Thailand, specifically investigating whether futures lead or lag those in the stock market, and the implications of such relations. For instance, in the last five years, futures trading volume in Thailand showed a stronger growth rate (70%) than the stock market's (68%). This study is of considerable significance because it will not only contribute to the limited body of knowledge regarding this relationship in emerging markets, but it will also provide valuable insights for market participants and policymakers in Thailand. A comprehensive understanding of the lead-lag relationships in these markets can inform investment strategies, improve risk management practices, and assist regulatory bodies with creating policies that promote market efficiency and stability (Khan et al, 2022).

Principally influencing the lead-lag relationships between the futures market and the stock market is information asymmetry. Information asymmetry is significant in financial markets as it creates an imbalance of information between parties involved in transactions. This imbalance can lead to moral hazard, where one party takes advantage of undisclosed information to the biases of the other, and adverse selection, where one party selectively conceals or reveals information to gain an advantage. These effects make it harder to set fair pricing and assess risk assessment. Many economists suggest that information asymmetry leads to market failure. It is one of the most significant problems that has a negative impact on people, from simple transactions to the financial crisis. Although it has a significant impact, it is difficult to resolve and remains unsolvable. In an efficient market, prices will be able to respond to all available market information instantaneously and simultaneously in every market. No investor has a competitive advantage over other investors. Therefore, the lead-lag of information asymmetry between the markets should not exist. However, there are investors who do not believe in a market's efficiency. They believe that informed investors have the potential for abnormal returns. There are numerous papers that argue the market is inefficient, one of them suggested that because of the cost of information (Grossman and Stiglitz, 1980), prices cannot effectively reflect the information that is accessible. Investors with private information has the option of trading on the futures market and the stock market, but futures markets are more attractive to investors than spot markets since they permit short selling and have lower transaction costs, Black (1975). The futures market also offers several advantages, including leverage, the opportunity for speculation, arbitrage, and hedging.

When Information asymmetry is high, informed investors will trade aggressively and generate trading volume (Glosten and Milgrom, 1985). Trading volume is commonly acknowledged as a proxy for the arrival of private information, and it allows us to comprehend how each type of investors process and respond to the arrival of private information. In situations where there is a substantial probability of an information asymmetry, order imbalance will be significantly higher. Order imbalance has become a widely used tool for traders to gain insights into the behavior of investors and make informed trading decisions. Chordia et al. (2019) began using the volatility of order imbalance (VOIB) as a new proxy for the costs of information asymmetry. Volatility of order imbalance has a positive correlation with adverse selection costs which is one of the major issues of information asymmetry. Moreover, Huang, H.-G et al., (2021) and Chordia et al. (2019) found that the volatility of order imbalance accurately captures the costs of information asymmetry when trading against informed investors in a wide range of situations. Volatility of order imbalance can capture information asymmetry better than order imbalance alone because it shows how the trading intentions of market participants and how supply and demand change over time. This makes it a more nuanced way to measure possible information asymmetry.

1.2 **Objectives and Research Hypothesis**

Objective of the Study is to contribute to the literature on lead-lag relationships in emerging markets. This paper will identify and analyze the existence of a lead-lag relationship between the volatility of order imbalance (VOIB), a proxy of information asymmetry, between the futures and stock markets in Thailand for each type of investor which fall into three categories: Foreign Investors (FI), Local Institutions (LS), and Local Investors (LI). This paper also provides insight into how a better understanding of this relationship can inform investment strategies, improve risk management practices, and regulatory legislation. This paper examines a Vector Auto-Regression (VAR) model to test the null hypothesis and alternative hypothesis. The hypothesis of a lead-lag relationships between VOIB in the future market and the stock market in a VAR model suggests that changes in VOIB in the future market can lead or lag changes in stock market, indicating a potential causal relationship or predictive power of future market VOIB and stock market movements for each type of investor.

This study focuses on information asymmetry, a topic that is less explored. This study is the first study that examines the lead-lag relationship of information asymmetry between markets via the lens of the cost of information or VOIB. Information asymmetry is difficult to quantify. Motivated by Chordia et al. (2019) study, measuring the VOIB may be simpler than directly measuring information asymmetry. Another motivating study is Kyle (1984), which indicates that the order of investors is a major indicator that investors are attempting to extract private information.

Huang, H.-G et al., (2021) is perhaps one of the studies that is closest to our analyses. In this study, the authors analyze Taiwanese market data to study if there are lead-lag relationships between the VOIB in TAIEX futures and the TWSE index. They find that for foreign investors, the VOIB of TAIFEX futures market leads the VOIB of stock market, whereas there is no correlation between the VOIB of local investors and local institutions between the two markets.

1.3 Scope of the Study

This study focuses on the Thailand Futures Exchange (TFEX) and the Stock Exchange of Thailand (SET) to conduct a comprehensive analysis of trading activity on the futures and stock markets of Thailand. Using VOIB as a proxy for information asymmetry, the purpose of this study is to explain the origins and trends of private information reflection across these markets and to provide a comprehensive understanding of the associated information risk for various investor types.

The application of VOIB as an indicator of information asymmetry and the existence of private information is the primary focus of the study. This study examines the idea that VOIB is directly influenced by external parameters that increase adverse selection costs, and that periods of high VOIB potentially signal the presence of more active informed traders and increased adverse selection. The study will try to highlight how the creation and release of private information contributes to increased volatility and consequently increased trading volumes and intensified volatility shocks.

The area of interest of the study is determined to the period from January 2017 to December 2022. TFEX and SET trade data provided by SETSMART will be analyzed within this time frame. The wide range of investor types represented in the data set will allow for the identification of trading patterns associated with the three main types of investor groups: Foreign Investors (FI), Local Institutions (LS), and Local Investors (LI). Furthermore, the study will employ a technique known as vector autoregression (VAR) to identify a lead-lag relationship between the trading activity in the futures and stock markets. This statistical approach is designed to provide insight on how information asymmetry between these markets influences the speed and efficiency of private information reflection in each, and the degree of interlinking between the two markets. Furthermore, this paper contributes to the limited body of research by employing impulse response functions and variance decomposition techniques to examine the outcomes resulting from shocks. These analyses provide insights into potential contagion effects and market segmentation. By studying the response patterns and decomposing the variations, this study aims to shed light on the interconnections and dynamics within the market, offering valuable information for understanding the transmission of shocks and their implications on market behavior.

Overall, this study may assist investors, market makers, regulators, and policymakers better understand the complex relationships that are present within Thailand's financial markets.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the data. Section 4 explains the methodology used in this study.

2. Literature review

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a significant concept in finance and economics, suggesting that financial markets reflect all known information, and therefore always trade at fair value. It implies that it's impossible to consistently achieve superior returns in the market, as price adjustments are instantaneous upon the release of new information. Industry professionals have studied the Efficient Market Hypothesis (EMH) for a long time. The broad research interest can be attributed to a variety of factors. To begin, there is a common assumption of higher risk-adjusted returns in inefficient markets. Therefore, research on the stock market's efficiency is essential for both individual and institutional investors. An in-depth understanding of market efficiency is also required for business leaders, as their decisions have an important effect on the perceived value of their companies. Furthermore, the EMH can be used to model the evolution of the stock market, which is important for market operators and regulators. Also, the hypothesis serves as the basis for many financial models. In recent years, the focus in academics and the professional sector has turned to behavioral finance theory, but this change does not reduce the importance of the EMH.

The Efficient Market Concept

The Efficient Market Hypothesis (EMH) is applicable to capital markets. Capital market efficiency is mainly related to cost efficiency, but other markets are usually examined from a perspective of allocation efficiency (Blume, Durlauf, 2008). Broadly, a market is considered efficient when stock prices accurately mirror fundamental company data. This means that any fluctuations in a company's market value should align closely with changes in its intrinsic value. However, these changes do not always correspond with the value and don't always hinder the trade of financial assets. Differences in investor knowledge and inconsistent transaction costs can impede immediate and full reflection of intrinsic value changes in market prices (Goedhart, Koller, Wessels, 2010). Nonetheless, if markets are efficient, algorithms will not record price changes in assets, and any excess returns are viewed as the result of success rather than a prediction coming true. Allen, Brealey and Myers (2011) classified a market as efficient if it was impossible to earn a return that surpasses the market return. This means that a share's value reflects the fair value of the firm and is equal to the future discounted cash flows considering the alternate cost of capital. According to Eakins and Mishkin (2012), an efficient market is one in which asset prices completely represent all available information. In essence, an efficient market is founded on two principles: 1) in efficient markets, all available information is already contained in stock prices; 2) in efficient markets, investors cannot make a risk-adjusted excess return.

When assessing the information that market prices reflect, market efficiency is commonly segmented into three tiers: weak, semi-strong, and strong forms of efficiency. In weakly efficient markets, the current stock price embodies all past-related information such as prior prices, trading volume, and so forth. It then becomes impossible to generate excess profit in such a market, rendering technical analysis unprofitable if the market is weakly efficient. Semi-strongly efficient markets, on the other hand, reflect not just historical prices but all currently available public information like acquisition announcements, dividend declarations, and changes in accounting policies. Lastly, strongly efficient markets incorporate all possible information, whether public or not, into current stock prices. This efficiency level implies that extra profit through insider trading is impossible, however some argue that it is possible (Malkiel, 2011). However, other academics claim that strong efficiency is achievable because insider trading is illegal (Schwert, 2003). Numerous empirical studies validate weak market efficiency in various capital markets, and this efficiency form is integral to stock and option valuation assumptions (Palan, 2004). The findings from semi-strong market efficiency studies differ substantially, while the strong market efficiency form remains largely unexplored, with the limited results pointing towards market inefficiencies (Mishkin, Eakins, 2012).

The EMH has significant ties to other financial assumptions and models. Foremost, total or partial rationality of market participants is required for market efficiency. It's commonly accepted that not all participants act rationally, leading to some trades being devoid of rational analysis. However, irrational investor trades are considered random and should have no effect on stock prices. For example, a random purchase that positively impacts share prices will be offset by a random sale, given equal chances of random buying and selling (Shleifer, 2000). Regarding trading styles, investors can be categorized as informed investors or noise traders. Informed investors base their decisions on fundamental analysis, while noisy traders ignore some available information while trading. According to Goedhart, Koller, and Wessels (2010), investors can be classified as intrinsic value investors, traders, or mechanical investors. Intrinsic value investors base their trading decisions on fundamental analysis, traders utilize technical analysis, and mechanical traders follow set rules like index replication. According to Goedhart, Koller and Wessels' (2010) research, intrinsic value investors significantly affect stock prices through concentrated and large trades. Thus, although the presence of irrational investors is widely acknowledged, their impact on stock prices is generally deemed inconsequential. This notion is closely tied to the arbitrage theory, which posits that irrational investors provide risk-free profit chances for others. Investors with experience use these opportunities to trade mispriced securities and correct illogical pricing. The EMH also has strong connections to the Capital Asset Pricing Model (CAPM) and the theory of securities substitution. The CAPM is frequently used to assess risk when testing the efficient market hypothesis.

Evolution of the Efficient market concept

In the 17th and 18th centuries, math, biology, physics, and logic were where the first sounds of the random walk theory were heard (Sewell, 2011). Today, the random walk theory is an important part of financial theory (Sewell, 2011). Particularly, the economic aspect of the efficient market hypothesis began to take shape at the close of the 19th century. De Moor, Van den Bossche, and Verheyden (2013) cite G. Gibson as the originator of the efficient market theory. In his 1889 book, Gibson argued that stock prices reflect the insights of the most perceptive market participants. In Gibson's view, stock valuation was a democratic process in which the direction of stock price changes was determined by the brightest participants, who were rewarded financially for their accurate predictions.

In 1900, French mathematician L. Bachelier theorized in his publication ‘Theory of Speculation’ that the expected return on any investment is invariably zero (Sewell, 2011). The first half of the 20th century saw several critical pieces of work attempting to establish the unpredictable nature of stock prices. For instance, K. Pearson, in 1905, became the first to employ the term random walk, although in the field of biology, not finance. In 1925, F. MacCauley made comparisons between the stock market and the flip of a coin. A. Cowles, an American economist, examined the trading statistics of professional investors in 1933 and concluded that they were unable to predicting future prices and securing excessive profits. He repeated the same point in 1944 after analyzing U.S. stock market data. These post-Great Depression works were unavoidably shaped by the widespread distrust towards financial markets and analysts at the time. The rapid development of economic theory during this period was heavily influenced by J.M. Keynes' work. Although Keynes primarily aimed to explain real economy developments, he also offered valuable insights into financial markets and asset prices. In 1923, Keynes suggested that the gains of investors stemmed not from superior foresight but from the heightened risks they undertook. In contrast, his 1936 publication, The General Theory of Employment, Interest and Money, suggested that stock market trades were driven more by primitive instincts than rational thought. This proposition appears more consistent with behavioral finance than the efficient market theory.

The EMH enjoyed its peak in the 1980s, primarily due to the seminal work of the American economist E.F. Fama (Shiller, 2003). Fama verified the randomness of stock prices in 1965 and introduced the concept of an efficient market for the first time. He insisted that the evidence supporting the EMH was so strong that it could only be ignored by substantial empirical studies (Fama, 1965). In 1967, H. Roberts officially introduced the term efficient market hypothesis and split market efficiency into strong and weak forms. Fama later extended this separation in 1970, who added the semi-strong form of market efficiency. He described an efficient market as one where information is fully reflected and suggested testing market efficiency in alignment with asset pricing tests (Fama, 1970). Although academics widely accepted the concept of market efficiency, professionals were largely unaware of it until B. Malkiel published A Random Walk down Wall Street in 1973. This publication sparked an EMH frenzy among professionals (Shiller, 2003). However, by 1976, S. Grossman highlighted the paradox of market efficiency: the more faith investors placed in market efficiency, the less efficient the market became. Grossman argued that if market participants unanimously believed in market efficiency, they would adopt a passive stance and stop gathering information, leading to market inefficiency.

Towards the late 20th century, many EMH studies started questioning its premises. In 1980, S. Grossman and J. Stiglitz contended that markets could never be truly efficient as information comes with a cost. Hence, the return on investment must exceed the cost of information, otherwise the incentive to invest would vanish. U.S. economist R. Shiller challenged the EMH with the concept of excess volatility, suggesting that the actual volatility of stock prices exceeded the volatility predicted by fundamental information. De Bondt and Thaler (1985) seconded Shiller's hypothesis of excess volatility, arguing that people tend to overreact to company news, which in turn affects stock prices. The EMH was dismissed by B. Lehmann and N. Jegadeesh in 1990 (Sewell, 2011). Fama (1991) stated that it was unclear whether seemingly predictable returns were due to market inefficiency or incorrect assumptions in asset pricing models. Even as criticism increased against the EMH, studies validating its premises persisted. K. Chan concluded in 1997 that global stock markets exhibited weak-form efficiency. In 1998, Fama suggested that overreaction was just as prevalent as underestimation in stock markets, thereby not causing inefficiency. Despite the declining popularity of the EMH due to increasing criticism, the concept of market efficiency remains a vital part in modern finance.

The modern approach to the Efficient market concept

The weak-form efficiency argument traditionally relies on the independence of returns, commonly evaluated through correlation. A study by Allen, Brealey, and Myers (2011) implies that today's stock return does not influence tomorrows. Although some may argue that one day isn't sufficient to uncover potential dependencies, the same authors found consistent results when examining weekly returns (Allen, Brealey, and Myers, 2006). Tests of serial correlation have repeatedly supported the Efficient Market Hypothesis (EMH) when assessing returns of both individual stocks and equity indices (Parks, Zivot, 2006). Predictability of stock markets can be tested using technical analysis trading rules, but these often fail to deliver steady surplus returns (Schleifer, 2000). Parks and Zivot (2006) posited that technical analysis would be profitable only in the absence of transaction costs. While academic circles may not favor technical analysis, professionals continue to use it widely (Mishkin, Eakins, 2012), suggesting that academic research may not be utilizing these methods to their fullest potential.

Another support for weak-form efficiency lies in prompt and accurate stock price adjustments following major announcements (like mergers, acquisitions, divestitures, or stock splits). Examination of stock price changes post-announcement, known as event studies, has repeatedly indicated the presence of semi-strong market efficiency. Shleifer (2000) found that price adjustments aligned with the semi-strong form of market efficiency when he analyzed aggregated data on investor responses to corporate news. He observed a stock price drift before the actual announcement, indicating market anticipation or information leaks. On the day of the announcement, the stock price typically leaps or plummets to its new intrinsic value, remaining relatively stable for at least a month. Shleifer (2000) proposed that this rapid, accurate price change is not followed by further price corrections. However, the accuracy and timeliness of price corrections remain contested among academics, citing barriers such as irrational market participants, inequities in information accessibility, and varying transaction costs. Event studies can also explore the stability of stock prices in the absence of corporate news, as exemplified by Scholes (1972).

The comparison between active and passive portfolio management lends further support to the EMH. If active portfolios can't outperform passive ones, gathering market information becomes unprofitable, suggesting market efficiency. A study by Allen, Brealey, and Myers (2011) showed that U.S. mutual funds outperformed their benchmarks in only 16 out of 47 studied years. The overall excess profit was small or negative, consistent with market efficiency. Malkiel (2003; 2011) found that a significant portion of mutual funds, around 70% from 1991 to 2001 and 66% from 1970 to 2010, underperformed compared to their benchmarks. Few funds consistently outperform, and those that do may be influenced by data aggregation. Malkiel (2011) noted that funds profitable in the short term didn't maintain this profitability in the long term. Moreover, top-performing fund managers one year typically produced average returns the next, a result in line with market efficiency.

Contradictions to the EMH also stem from the irrational behavior of market participants, a topic extensively explored in behavioral finance. Particularly, this irrationality isn't restricted to inexperienced investors. Coval and Shumway (2005) identified loss aversion as the most common pattern of irrational investor behavior, suggesting investors tend to be more risk-averse at the start of the day, a finding made by Bailey, Kumar, and Ng (2011). Such irrational behavior can result in short-term stock price anomalies and long-term asset bubbles. Shiller (2003) attributed asset bubbles to feedback effects. Malkiel, Mullinathan, and Stangle (2005) believed that asset bubbles develop when investors are unable to maintain a short position in overvalued assets due to increasing losses. Thus, irrational behaviour provides a significant challenge to the EMH by casting doubt on the ability of investors to accurately assess and react to mispriced securities.

2.2 Order imbalance (OIB)

Stoll (1978) suggests a model wherein market makers, like other investors, maintain portfolios with a desired risk and return. Providing immediate trade execution diverts their portfolios from the preferred state, causing them to take on unwanted risks. This model suggests a direct correlation between order imbalance and subsequent changes in asset prices. For instance, a market maker carrying more stocks than desired (a long position) implies a negative order imbalance, caused by more sell than buy orders from traders. The market maker then lowers quotes to encourage buying (and deter selling) which drives the stock price down, resulting in negative returns. Assuming no fresh information, prices revert once inventory is offloaded, leading to a negative correlation between order imbalance and future stock prices. Similarly, Roll (1984) proposes that market makers' actions create negative autocorrelation in stock prices. In a market without intermediaries, if prices are efficient and trading costs non-existent, all price changes should reflect new information, hence price changes shouldn't be autocorrelated. However, with intermediaries like market makers demanding compensation, bid-ask spreads occur and cause negative autocorrelation. Sell orders lead to negative order imbalance and subsequent trades at higher (or equal) prices, correlating negatively with future returns. In Kyle's well-known model from 1985, informed traders who cause order imbalances, consider the impact of their trades on future prices. To maximize profits from their privileged information, they split their trades and gradually skew the market until the asset price aligns with their private information. This behavior results in autocorrelation in trades and order imbalances, which strengthens Stoll's inventory holding effect.

Building on Kyle's model, Chordia and Subrahmanyam (2004) propose that informed traders seeking to minimize price impact divide their orders over time. This creates autocorrelation in order imbalances, continuous price pressure and subsequent price increase. If no new information arises, once informed traders reach their target, prices should return to initial levels. Moreover, Chordia and Subrahmanyam (2004) argue that controlling for current order imbalance, past imbalances should negatively relate to returns. The rationale is that trades related to historical and new information equally influence price pressure. However, trades related to past events should carry less weight since their information content and associated price effects have been partially revealed. Recent studies by Chordia et al. (2019) connect order flow variation to the cost of information asymmetry, proposing that order flow volatility can stand in for private information costs. They suggest that high order flow volatility implies increased activity by informed traders, thus increasing the cost of adverse selection. Market makers interpret the likelihood of dealing with an informed trader based on order flow imbalances and adjust bid-ask spreads accordingly. Bogousslavsky and Collin-Dufresne (2022) studied high-frequency inventory risk of market makers via an order imbalance model. Their theoretical model suggests that high trade volume could either reduce or increase the market maker's inventory risk and hence spreads, depending on whether it leads to offsetting trades or volatility in inventory shocks.

Initial studies on order imbalance concentrated on brief periods such as Black Monday (as per Blume et al., 1989), distinct occurrences like earnings announcements (referenced by Lee, 1992), or a limited selection of stocks (as explored by Brown et al., 1997). These early research efforts concluded that order imbalance significantly influenced stock returns both immediately and over time, although they lacked robust theoretical foundations. It was observed that the impacts of order imbalance could affect returns on the following trading day, with some evidence pointing to effects even on the subsequent trading day. Expanding the timeframe beyond singular events, Stoll (2000) examined the impact of order imbalance on stock returns for NYSE and NASDAQ stocks from December 1997 to February 1998. Their findings showed a significant positive correlation between immediate order imbalance and stock returns. However, when considering immediate order imbalance, the effect of previous order imbalances on stock returns was less significant in their sample. Similarly, Chan and Fong (2002) explored the relationship between volume volatility and order imbalance, focusing on NYSE and NASDAQ stocks over a six-month period. Their findings suggested a significant and positive predictive relationship between order imbalance and immediate returns, after adjusting for factors like past returns and weekday-specific effects.

Chordia et al. (2002) were the first to look at how order imbalances affect stock returns over a longer length of time. They based their model on the market maker's inventory dilemma, following Stoll's (1978) inventory model. They discovered that order imbalance could be attributed to numerous factors, including shifts in macroeconomic variables and weekday-specific trading patterns. Additionally, they found a substantial positive immediate effect of order imbalance on returns, leading eventually to price reversals, especially following days with significant negative returns. Building on this, Chordia and Subrahmanyam (2004) found that their empirical results aligned with their model discussed in Section 2.1. In their NYSE stock sample, order imbalances were positively autocorrelated, leading to previous order imbalances positively influencing current returns due to price pressures. Moreover, they found that when considering immediate order imbalance, past imbalances negatively correlated with current stock returns, consistent with their theory. This finding was most prominent in the three smallest size quartiles. Shenoy and Zhang (2007) for Chinese stocks, and Hanke and Wiegerding (2015) for German stocks, later agreed with these results.

2.3 The volatility of order imbalance (VOIB)

Order imbalance is a situation in financial markets where the volume of buy orders surpasses the volume of sell orders, or vice versa. This imbalance often leads to volatility in the prices of financial instruments. The volatility of order imbalance refers to the fluctuation in the degree of imbalance over a given time period. If the imbalance is changing rapidly (large buy orders followed by large sell orders, or vice versa), then the volatility of order imbalance is high. Conversely, if the imbalance is relatively stable (consistent buy or sell pressure), then the volatility of order imbalance is low.

Trading activity is fundamental in aiding the price discovery process. Among various standard trading metrics, such as trading volume or turnover rate, order imbalance, or net buy orders, serves as a prevalent indicator of collective investor interest, forging substantial connections between trading activity and asset returns (refer to works by Chordia and others). Order imbalance also effectively measures the adjustment of market makers' inventory positions and provides insights into future price trends. For instance, in one scenario, a significant order imbalance can stress a market-maker's inventory, leading to increased quoted prices. In another situation, a large order imbalance also significantly impacts price. Consequently, numerous earlier studies have employed order imbalance to gauge the informational value of trading activity. Recognizing the wide application of order imbalance in both previous and contemporary research, Chordia, Hu, Subrahmanyam, and Tong (2017) offered both theoretical and empirical evidence to propose the volatility of order imbalance (VOIB), or the standard deviation of daily order imbalances, as a fresh indicator of the costs related to information asymmetry. Greater volatility in order imbalance suggests that informed traders are more active in the market, leading to increased adverse selection costs for market makers or uninformed investors.

Many studies have compared the informational value of trading for foreign and domestic investors in the same market, but the results are somewhat inconsistent, likely necessitating further validation. Some research indicates that domestic investors are better informed, while others suggest that foreign investors possess superior information. With our newly developed measure of order imbalance volatility, we contribute to this ongoing debate by analyzing the informational value of trading activities across various investor groups in the Thailand market.

Chordia et al. (2017) demonstrated that order flow volatility serves as an indicator of the costs associated with information asymmetry. They established a positive correlation between order flow volatility and metrics of adverse selection costs. They further suggested that incrased order flow volatility indicates increased activity by informed investors in the market, leading to greater information asymmetry in transactions.

2.4 The lead-lag relationships between markets

Lead-lag relationships between markets refer to a situation where the price movement in one market precedes (leads) or follows (lags) the price movement in another market. This often occurs between related markets, such as between different geographic markets, different financial instruments, or between the physical and futures markets of a given commodity. For example, the US stock market may react to an economic announcement more quickly than the European stock market due to time zone differences, leading to a lead-lag relationship. Similarly, the futures market for a commodity may react to new information more quickly than the physical market for the same commodity, leading to another lead-lag relationship.

The lead-lag relationship can be exploited by traders and investors through strategies like arbitrage. For example, if the price of a commodity in the futures market rises before the price in the physical market does, a trader could buy the commodity in the physical market and sell it in the futures market to profit from the price difference. Understanding lead-lag relationships can also be helpful in portfolio management and risk management. By identifying and understanding these relationships, portfolio managers can better anticipate price movements and adjust their positions accordingly. Similarly, risk managers can better understand and manage the risks associated with these relationships. In addition to market-to-market lead-lag relationships, there are also lead-lag relationships within a single market. For example, within the stock market, the stocks of large companies often lead the stocks of smaller companies. This is because large companies are often more closely followed by investors and analysts, and their stocks tend to react more quickly to new information.

There are several factors that can influence the lead-lag relationship between markets, including differences in market hours, differences in the speed at which markets react to new information, and differences in the availability and accuracy of information in different markets. Additionally, regulatory differences between markets can also influence the lead-lag relationship. However, it's important to note that these relationships are not static and can change over time. For example, improvements in technology can speed up the transmission of information, reducing the time lag between markets. Similarly, regulatory changes can affect the speed at which markets react to new information. Therefore, traders and investors need to constantly monitor and reassess these relationships.

A significant portion of the literature on derivatives markets looks at the influence that the inception and presence of these markets have on the stability of their corresponding cash markets. These influences could take the form of the derivatives trading's effects on cash price volatility, market depth, information integration, price discovery, and risk transfer, among others. The focus of this paper is the rate at which information is processed in cash and futures markets, specifically examining the transfer of information in returns and volatilities between these two markets in a newly formed derivatives market. In essence, by looking at the leading and trailing relationship between price changes in stock index futures returns and the returns of the underlying cash market, we can ascertain how rapidly each market absorbs new information and how closely interconnected the two markets are.

Both futures and cash index prices are representative of the aggregate values of the underlying stocks. Differences in carrying costs, however, can lead to differences between futures and cash prices. In a world without frictions, where interest rates and dividend yields are non-stochastic, price movements in the two markets would be perfectly correlated simultaneously and show no cross-autocorrelation (Chan, 1992). Therefore, in perfectly efficient futures and cash markets, informed investors wouldn't favor one market over the other, and new information would be incorporated into both simultaneously. However, if one market absorbs information faster than the other due to market frictions, such as transaction costs or microstructure effects in capital markets, a lead-lag relation in returns can be seen. For example, the lead-lag relationship between FTSE/ATHEX-20 and FTSE/ATHEX Mid-40 stock index futures and their underlying cash indices in terms of both returns and volatilities within the derivatives market of Greece. This market is overseen by the Athens Derivatives Exchange (ADEX), established in April 1998.

ATHEX, an important market for international investors, is part of the Morgan Stanley International Index (MSCI). The ATHEX has witnessed rapid growth since the late nineties and has had a significant impact on the country's economic development. The emergence of a robust security market in the Greek economy has attracted a great deal of attention from both domestic and foreign investors. In 1997, the Greek economy sought to align its macroeconomic figures to meet the criteria to join the Euro Zone. Emerging capital markets have long been a puzzle for the field of finance. According to Bakaert and Harvey (1997) and Antoniou and Ergul (1997), returns from emerging markets are characterized by low liquidity, thin trading, higher sample averages, low correlations with developed market returns, non-normality, greater predictability, higher volatility, and short samples. Furthermore, market imperfections, high transaction and insurance costs, less informed rational traders, and investment restrictions may also influence the risks and returns involved. Investors in emerging markets may either overestimate their own forecasts, introducing bias into their actions, or may not react immediately to information. Therefore, returns in emerging markets may possess different attributes than those in developed countries.

In addition, the impact of introducing derivatives trading on the corresponding cash market has not been completely explored. With regards to the Greek stock market, Spyrou (2005) demonstrates that the establishment of derivatives markets contributes to the stability of cash markets, as it appears to decrease volatility in the latter following the launch of derivatives trading. Kavussanos and Visvikis (2007) reveal that ADEX derivatives contracts can effectively shift risk from those who prefer to avoid it to those market agents who are prepared to accept it. Kenourgios (2004) provides proof of a spill-over effect in the average cash and futures returns in the ATHEX–ADEX markets.

Consequently, an empirical examination of the leading and trailing relationship in returns and volatilities using derivatives contracts for this recently developed market is deemed essential. This would offer further evidence on the impact of derivatives trading in cash markets and potential spill-over of information in returns and volatilities between the markets.

The lead-lag relationship in returns and volatilities between stock index cash and futures markets also interests studies, practitioners, and regulators for various reasons. Firstly, this issue is tied to market efficiency and arbitrage. Secondly, futures markets are believed to play an important role in price discovery. If that's the case, futures prices should provide valuable information about upcoming cash prices, beyond what's already incorporated in the current cash price. A third issue relates to potential volatility spill-over effects of futures trading. If volatility spill-overs exist from one market to the other, then the volatility transmitting market could be used as a vehicle of price discovery by market agents. For instance, the instantaneous impact and lagged effects of shocks between cash and futures rates could be used in decision-making regarding hedging activities and budget planning. Moreover, if a return analysis is inconclusive, volatility spill-overs offer an alternative measure of information transmission.

2.5 The lead-lag relationships between investors

Certain patterns show up in the complex world of investment, providing insight into the decision-making processes of various investor groups. An interesting pattern that requires attention is the lead-lag relationship, which refers to a phenomena where certain groups of investors consistently execute their investment decisions before others. Typically, it is the local investors who frequently take the lead in these initiatives, Tanthanongsakkun (2018).

Local investors have a natural benefit due to the fact that they are familiar with their home market and are located in close proximity to it. Because of their extensive background in the local business community and the ease with which they can keep up with regional news and developments, they have a position that is unique. They are able to quickly spot even the most minute changes in the market, alterations in consumer behavior, or implications of regional policies—details that may take institutional investors or foreign investors longer to understand. When these local investors act, their decisions often serve as a subtle guide for others. For instance, a significant buy or sell action from a prominent local investors can be perceived as them having insightful knowledge, prompting others to take notice and evaluate their positions. Foreign and local institutional investors, with their vast resources, often keep a close eye on these local movements. They recognize that these early movers might be onto something, and adjusting their strategies in response can be beneficial.

The close relationship local investors have with their surroundings often allows them to lead in the market. Their actions, in turn, set off a ripple effect, influencing the strategies and decisions of other investors who look to them for cues on upcoming market trends.

3. Data

3.1 Observation and samples

The data derives from the Thailand Futures Exchange (TFEX) and the Stock Exchange of Thailand (SET), two officially recognized markets in Thailand, over January 1, 2017, to December 31, 2022 sample period. The TFEX provides us with a unique dataset of account-level transactions, and we use this data along with daily trading statistics on investors in the TFEX to construct the VOIB for the futures market. For the spot market, we construct the VOIB for each stock each month by collecting daily statistics of trading volume with trade direction data (buys and sells). All data of 2916 datasets were collected from SETSMART and the trade date that have insufficient daily trading data will be filtered out. The dataset includes complete trading data for every transaction. The data set consists of a position indicator, the trading direction (buy or sell), an investor identifier, a date, and the trading volume. Furthermore, being able to identify the different types of investors, we can also analyze and compare the different types of investors, which are foreign investors, local Institutions, and local investors.

3.2 Variables

Order imbalance (OIB)

The paper by Chordia, Roll, and Subrahmanyam (2002) concludes that trading volume has a significant effect on stock returns. They use order imbalance as a proxy of trading volume and reveal private data. Order imbalance has become a widely used tool for traders to gain insights into the behavior of investors and make informed trading decisions. Order imbalance can stand for the trading volume and reveal private information in financial markets due to the significant impact it has on the behavior of market participants. Large order imbalances can indicate a high level of demand for a particular security, which often leads to increased trading activity and higher trading volumes. Furthermore, investors who possess private information about the market may use order imbalances to execute trades based on their private information. These trades can result in significant price movements, which in turn create opportunities for profit.

In this paper, we will calculate daily order imbalance for each type of investor based on the number of buys and sells. The daily order imbalance (OIB) for each type of investor is defined as follows:

$$OIB_{i,k} = \frac{B_{i,k} - S_{i,k}}{B_{i,k} + S_{i,k}} \quad (1)$$

where $\boldsymbol{OIB_{i,k}}$ is the order imbalance in day i of trader group k

$\boldsymbol{B_{i,k}}$ is the buy volume in day i of trader group k

$\boldsymbol{S_{i,k}}$ is the sell volume in day i of trader group k

The volatility of order imbalance (VOIB)

We based our measure on a model from Kyle (1984, 1985) and Subrahmanyam (1991), which demonstrates that both volatility of order imbalance and adverse selection costs of private information are positively related to variables that capture information in financial markets. Model is holding market maker risk aversion constant, changes in all the other exogenous parameters affect adverse selection costs of private information and the volatility of order flow in the same direction. The volatility of order imbalance has become a potential indicator in discovering private information in financial markets. Unlike order imbalance alone, which represents the net difference between buy and sell orders, the volatility of order imbalance captures the dynamic nature of market participants' actions and the intensity of trading activity. Private information can lead to sudden shifts in trading sentiment and imbalances in buy and sell orders. By considering the changes and fluctuations in order flow imbalance over time, the volatility of order imbalance provides a more timely and sensitive measure of these shifts. Moreover, it reflects the speed at which market participants adjust their positions and the changing dynamics of supply and demand. The volatility of order imbalance offers a clarified signal for identifying the presence of private information.

In the papers from Huang, H.-G et al., (2021) study the significance of the order imbalance (OIB) in both short and long horizontal markets. They concluded that the order imbalance (OIB) is more effective in predicting short horizontals after finding that the impact of the order imbalance (OIB) on the market at the monthly horizon is weaker in significance than at the weekly horizon. Chordia and Subrahmanyam (2004) also gave their support to this finding. In addition, Huang, H.-G et al., (2021) concluded that the order imbalance volatility (VOIB) is more accurate when used to long horizontal or monthly horizon. The order imbalance volatility (VOIB) is construct as the standard deviation of daily OIB_i in the same month. The monthly VOIB for each type of investor is defined as follows:

$$VOIB_{t,k} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(OIB_{i,t,k} - \overline{OIB_{\iota,t,k}}\right)^2} \qquad (2)$$

where $\boldsymbol{VOIB_{t,k}}$ is the volatility of order imbalance in month t which has N trading days of trader group k

$\boldsymbol{OIB_{i,t,k}}$ is the order imbalance in day i in month t of trader group k

$\boldsymbol{\overline{OIB_{\iota,t,k}}}$ is the mean of all daily OIB in month t of trader group k

3.3 Data descriptive

The summary statistics on trading volume by the different types of investors are presented in Table 1. Panel A of Table 1 shows that on the spot market, foreign investors have the highest average daily trading volume of the three investor types from 2019 to 2022. The average daily trading volume in all stocks (in millions of shares) in 2022 by foreign investors was 67,784, compared to 11,063 by local Institutions and 48,415 by local investors. Referring to Panel B of Table 2, the results of the futures market show the average daily trading volume for foreign investors was 270,962 contracts, the average daily trading volume for local institutions was 324,556 contracts, and the average daily trading volume for local investors was 517,983 contracts. During our sample period, the biggest investor group in terms of daily trading volume in the futures market consisted of local investors, which differs somewhat from the results reported in Panel A of Table 1 for the spot market.

Table 1: Descriptive statistic of trading volume in future market and stock market.

Note: The table reports the summary statistics of all 1,458 days which include the average daily trading volume of stock and future markets from 2017-2022

Variables	**The average daily trading volume**					
	2017	**2018**	**2019**	**2020**	**2021**	**2022**
Panel A: Stock market daily trading volume (in units of million shares)						
Foreign Investors (FI)	5,611	8,258	12,628	14,342	23,179	67,784
Local Institutions (LS)	632	606	600	729	685	11,063
Local Investors (LI)	9,324	10,189	8,684	12,667	21,102	48,415
Panel B: Index futures market daily trading volume (in units of contracts)						
Foreign Investors (FI)	68,483	111,832	152,170	227,393	253,095	270,962
Local Institutions (LS)	244,886	306,430	282,938	281,338	343,084	324,556
Local Investors (LI)	325,228	423,042	407,881	466,536	510,663	517,983

Table 2: The summary statistics on VOIBs across the three types of investors.

Note: Panel A reports the descriptive statistics on monthly VOIBs in the spot market from January 2017 to December 2022. Panel B reports the descriptive statistics on monthly VOIBs in the future market from January 2017 to December 2022. VOIB is defined as the standard deviation in the daily order imbalance in a given month. FI, LS and LI respectively denote foreign investors (FI), local institutions (LS), and local investors (LI).

Variable	Observations	Mean	S.D.	Min	Max
Panel A: The volatility of order imbalance in the Spot market					
$VOIB_{F,Stk}$	72	0.0156	0.0080	0.0061	0.0500
$VOIB_{LS,Stk}$	72	0.1806	0.0377	0.1094	0.3082
$VOIB_{LI,Fut}$	72	0.0272	0.0135	0.0132	0.1142
Panel B: The volatility of order imbalance in the future market					
$VOIB_{F,Fut}$	72	0.0856	0.0234	0.0431	0.2891
$VOIB_{LS,Fut}$	72	0.1067	0.0309	0.0536	0.1950
$VOIB_{LI,Fut}$	72	0.1121	0.0454	0.0389	0.2891

The summary statistics on VOIBs across the three types of investors is presented in table 2. Panel A, VOIB of local institutions is the highest among three types of investors in the spot market, followed by local investors and foreign investors. Panel B, VOIB of local investors is the highest among three types of investors in the future market, followed by local institutions and foreign investors. Local institutions and local investors tend to be informed investors. Order imbalances, which represent the difference between buy and sell orders, tend to be more volatile when traders have specific information that prompts them to act decisively in one direction or another. When there's a big swing in buying or selling, it often means that the investor has specific information that encourages this behavior. By spotting and examining these high volatilities in order imbalances, we can identify the investors who likely have better or early access to private information, thus defining them as "informed".

In financial markets, VOIB is a key measure that observes variations in buying and selling pressures. When VOIB is high, it often suggests that there's a particular group of investors making substantial trades. These investors, who cause such imbalances, are frequently seen as "informed investors" because they might be acting based on exclusive, valuable insights about an asset that others don't possess.

The microstructure theory of financial markets provides a framework to understand this phenomenon. This theory delves into the behaviors and interactions of different market participants, recognizing that they don't all operate with the same set of information. Some have access to more detailed or timely information, giving them an advantage. When these informed investors act on their knowledge, they can place large orders that disrupt the usual balance of buy and sell orders. This disruption is what leads to the observed high VOIB. In essence, the microstructure theory supports the idea that high VOIB is an outcome of informed trading. It provides the foundation to understand that significant imbalances in order flow, indicated by increased VOIB, often result from the activities of investors who have a unique informational advantage.

In this section, we aimed to discern whether distinct types of investors exhibit significantly different behaviors from one another. Our focus was primarily on the VOIB across various market conditions. The methodology employed to ascertain these differences was the one-sample t-test, with the null hypothesis positing that there is no significant difference between the groups, i.e., the mean difference between the two groups is zero. Conversely, our alternative hypothesis postulated that this mean difference is greater than zero.

Our first analysis involved a comparison of the VOIB between local institutions and local investors within the spot market. The resulting t-value was 20.68. This value, lying in the extreme tail of the t-distribution, suggests a p-value so minute that it approximates 0. Given this result, we confidently reject the null hypothesis at even the strictest significance levels, such as 1%. Thus, we can deduce that the VOIB difference between local institutions and local investors in the spot market is not merely by chance. Next, we tested the VOIB of foreign investors against that of local investors, again within the spot market framework. This analysis yielded a t-value of 6.48. The p-value derived from this is notably less than 0.001, solidifying the significant disparity between these two investor groups at the 1% significance level. Lastly, we explored the VOIB dynamic between local institutions and local investors, but this time in the futures market. The t-value stood at 11.99, again pointing to a p-value smaller than 0.001. Like our previous findings, this underscores a statistically significant difference in the VOIB between these two groups, even at a stringent 1% significance threshold.

In summary, our analyses consistently highlight statistically significant variations in the VOIB among different investor groups across both spot and futures markets. These findings provide robust evidence for the hypothesis that different types of investors behave distinctively in their trading activities.

4. Methodology

The objective of this study is to examine the lead-lag relationships of information asymmetry between the future and spot markets. To conduct a comprehensive investigation of the lead-lag relationships, the Vector Autoregression (VAR) model will be employed. The Vector Autoregression (VAR) model enables the examination of the dynamic relationships among multiple variables at the same time. In implementing the VAR model, it is essential to conduct unit root tests on the variables, as the assumption of stationarity is fundamental to VAR analysis. With the implementation of this test, it is ensured that the variables present a stationary sequence, which allows for a precise analysis of the lead-lag relationship between the future and spot markets.

4.1 The unit root test

Testing for stationarity in time series data is important for accurate modelling, precise forecasts, and insightful conclusions. It ensures that statistical properties remain constant over time, allowing for the selection and estimation of appropriate models and variables. Non-stationarity can result in bias results and unreliable inference. Testing for stationarity is therefore an important step in time series analysis for producing valid and reliable research results.

This paper focuses on the application of the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) with an intercept and trend component in unit root analysis. The ADF test is a commonly employed statistical method for determining whether a time series is stationary or non-stationary. We allow for potential linear trends and overall level shifts in the data by incorporating an intercept and trend into the ADF test. This enables us to capture more complex dynamics as well as understand the long-term behavior of the investigated variables better. Next section of this paper will examine the lead-lag relationship between variables using a VAR model that require the stationary. The stationarity of the variables, as determined by the unit root test, becomes important in this context.

The main objective of this study is to analyze the stationarity of the volatility of order imbalance (VOIB), that serves as a proxy for information asymmetry. As an endogenous variable within our model, it has an important role in understanding the lead-lag relationship between the future and spot markets. The examination of the stationarity of VOIB is important in verifying its consistent behavior over a period of time, which allows for reliable and accurate modelling in the Vector Autoregression (VAR) framework.

The Augmented Dicky Fuller Test model with intercept and time trend is defined as follows:

$$\Delta Y_{t,k} = \beta_0 + \beta_1 t + \gamma Y_{t-1,k} + \sum_{i=1}^{n} \beta_i Y_{t-i,k} + \varepsilon_t \tag{1}$$

where $\boldsymbol{Y_{t,k}}$ is the volatility of order imbalance (VOIB) at time t of trader group k

$\boldsymbol{\beta_0}$ is the intercept term or constant in the regression equation

$\boldsymbol{\beta_1}$ is a coefficient for the linear trend in the data over time

$\boldsymbol{\gamma}$ is the coefficient presenting process root

n is the lag order of the first-differences autoregressive process

$\boldsymbol{\varepsilon_t}$ is the residual term or error component

The hypothesis for Augmented Dicky Fuller Test is defined as follows:

$$H_0: \gamma = 0$$
$$H_1: \gamma < 0$$

If the null hypothesis (H_0) is rejected, it implied the absence of a unit root and indicating stationarity in the time series. On the other hand, if the null hypothesis (H_0) is failed to reject, this could indicate the presence of a unit root, suggesting non-stationarity in the time series.

4.2 Vector autoregression (VAR) models

To investigate the lead-lag relationships between variables, such as the future and spot markets in our study, it is necessary to employ a suitable analytical tool known as the Vector Autoregression (VAR) model. This model helps us understand how changes in one variable affect another variable over time. It allows us to study the relationship and influences between these variables in a dynamic manner. The application of the VAR model enables the examination of causal relationships, identification of lead-lag variables, and explore how they interact with each other. This model is particularly helpful for figuring out the complicated relationships and correlations between different market measures. It gives us important information about how information spreads and how markets react to changes.

Unrestricted vector autoregression (VAR) model is an important tool for examining lead-lag relationships between variables. By employing an unrestricted VAR model, we can capture the full complexity of the interactions among the variables without imposing any specific constraints on the coefficients. This allows us to examine the dynamic relationships and temporal dependencies between the variables over time. By estimating the lagged values of each variable, the unrestricted VAR model enables us to identify the lead-lag patterns and understand how changes in one variable affect the others. This study focuses on examining the lead-lag relationships of VOIB between spot and future markets for different types of investors. To achieve this aim, we will employ the unrestricted vector autoregression (VAR) model to analyze these relationships.

Furthermore, we employ Akaike's information criterion (AIC) to determine the lag for variables. Our VAR model equations are divided into two sections. The first section focuses only on endogenous variables, highlighting their relationships while ignoring the impact of exogenous factors. This separation enables us to understand the internal dynamics and relationships of the endogenous variables in a clear and straightforward manner. In the second section, the equations include both endogenous and exogenous variables. This enables us to investigate the effect of exogenous variables on endogenous variables, considering their interdependencies and possible feedback effects. By including the exogenous variables in this section, we obtain an understanding of their direct and indirect effects on the system.

We examine six VAR equations in the first section, twice for each investor type at monthly horizons. One equation is for the lead-lag relationships of VOIB from the stock market to the future market, and another is for the lead-lag relationships of VOIB from the future market to the stock market. For the first section, VAR equations are defined as follows:

$$VOIB_{t,k,Fut} = \propto_1 + \sum_{i=1}^{l} \alpha_{fi}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \beta_{fi}^{k} VOIB_{t-i,k,Stk} + \varepsilon_{t,k,Fut} \qquad (2)$$

$$VOIB_{t,k,Stk} = \propto_2 + \sum_{i=1}^{l} \alpha_{si}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \beta_{si}^{k} VOIB_{t-i,k,Fut} + \varepsilon_{t,k,Stk} \qquad (3)$$

where $\propto_1$ and $\propto_2$ are the intercept terms or the constant values for the equations

$\boldsymbol{VOIB_{t,k,Fut}}$ is the monthly volatility of order imbalance in the future market of investor k at month t

$\boldsymbol{VOIB_{t,k,Stt}}$ is the monthly volatility of order imbalance in the spot market of investor k at month t

K is the types of investors, which are foreign investors (FI), Local Institutions (LS), and Local investors (LI)

$\boldsymbol{\varepsilon_{t,k,Fut}}$ and $\boldsymbol{\varepsilon_{t,k,Stk}}$ are the error terms or residual at time t

In the second section, Huang, H.-G et al., (2021) also mention that there are other variables that can explain VOIB. These variables will be included as exogenous in our model. It is important to include exogenous variables in a VAR model so that we are able to account for external factors that may influence the VOIB. These exogenous variables capture the impact of additional relevant factors that can affect the relationships and dynamics among the endogenous variable or VOIB. By including exogenous variables, we can improve the model's capacity for explanation, improve its predictive ability, and provide a more comprehensive understanding of the underlying phenomena. This ensures that our analysis considers all relevant factors and provides a more accurate representation of the relationships in the actual world that we are studying. In this study, we examine return, the change in total trading volume, illiquidity, and market return standard deviation as exogenous variables. Unit root tests are typically conducted to determine the stationarity of variables included in the VAR model. However, for exogenous variables, the assumption is that they are already stationary, either due to theoretical reasons or based on prior empirical evidence. Therefore, there is no need to run unit root tests for exogenous variables within the context of the VAR model. The objective of the VAR model is to examine the relationship between exogenous variables and the VOIB for each type of investor. Particularly, we aim to examine whether exogenous variables have a significant impact on the behavior and dynamics of VOIB for each type of investors.

We examine six VAR equations in the second section, twice for each investor type at monthly horizons. One equation is for the relationships between exogenous variables and VOIB the future market, and another is for relationships between exogenous variables and VOIB the market. For the second section, VAR equations are defined as follows:

$$VOIB_{t,k,Fut} = \propto_3 + \sum_{i=1}^{l} \alpha_{fi}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \beta_{fi}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \gamma_{fi}^{ret}\, Ret_{t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{vol}\, \Delta\mathrm{Vol}_{t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{IIliq}\, IIliq_{\ t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{SDRet}\, SDRet_{t-i,Fut} + \varepsilon_{t,k,Fut} \tag{4}$$

$$VOIB_{t,k,Stk} = \propto_4 + \sum_{i=1}^{l} \alpha_{si}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \beta_{si}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \gamma_{f=si}^{ret} Ret_{t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{vol} \Delta \mathrm{Vol}_{t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{IIIiq} IIIiq_{\ t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{SDRet} SDRet_{t-i,Stk} + \varepsilon_{t,k,Stk} \tag{5}$$

where $\propto_{\mathbf{3}}$ and $\propto_{\mathbf{4}}$ are the intercept terms or the constant values for the equations

$\boldsymbol{Ret_{t-i,Fut}}$ and $\boldsymbol{Ret_{t-i,Stk}}$ are the monthly return in the future and spot markets at month t

$\boldsymbol{\Delta \mathrm{Vol}_{t-i,Fut}}$ and $\boldsymbol{\Delta \mathrm{Vol}_{t-i,Stk}}$ are the monthly change in total trading volume in the future and spot markets at month t

$\boldsymbol{IIIiq_{\ t-i,Fut}}$ and $\boldsymbol{IIIiq_{\ t-i,Stk}}$ are illiquidity in the future and spot markets at month t

$\boldsymbol{SDRet_{t-i,Fut}}$ and $\boldsymbol{SDRet_{t-i,Stk}}$ are the standard deviation in the market returns in the future and spot markets at month t

$\boldsymbol{\varepsilon_{t,k,Fut}}$ and $\boldsymbol{\varepsilon_{t,k,Stk}}$ are the error terms or residual at time t

Return variables (Ret) refer to the measures or indicators that capture the price fluctuations or changes in value of a financial instrument over a specific time period. Return variables are commonly derived from historical price data and can be calculated using logarithmic returns. An illiquidity (Illiq) can be used as a general indicator of price impact because it represents the daily price response connected to a dollar of trading volume over a specific period of time. An illiquidity reflects the effect of order flow on pricing, the concession a seller makes or the premium a buyer pays when executing a market order, that results from adverse selection costs according to Amihud and Mendelson (1980) and Glosten and Milgrom (1985). This variable is the monthly average ratio of the daily absolute return divided by the total trading multiplied by 10^4 in coefficient adjustment. This ratio gives the absolute (percentage) price change per dollar of daily trading volume, or the daily price impact of the order flow. The change in total trading volume (ΔVol) is the percentage change in a financial instrument's total trading volume between two periods. The total trading volume variable shows market activity changes. It shows how market conditions and investor behavior change trading interest and participation between two periods. The standard deviation in the market returns (SDRet) is a statistical measure that quantifies the volatility or variance of market returns as a whole. It is a commonly employed metric for assessing the level of market investment risk. A greater standard deviation indicates that market returns tend to fluctuate more widely, thereby indicating greater market volatility and potential investment risk. In contrast, a lower standard deviation indicates more predictable and stable market returns. When evaluating the risk and potential return of investment opportunities, investors and analysts frequently use the standard deviation of market returns as a key metric.

In this model, the F-test will be applied to the coefficients of lagged independent variables. The F-test determines whether the addition of lagged variables significantly improves the explanatory power of the model. This test enables us to assess the causal relationship and constant interactions between the VAR model's variables. This study focuses mainly on examining the VOIB relationships between future and spot markets for each type of investor. Our primary hypothesis in this context focuses on the Beta coefficient.

The hypothesis for equations (2) is defined as

H_0: $\beta_{f1}^{k} = \beta_{f2}^{k} = \ldots = \beta_{fi}^{k} = 0$
H_1: at least one of the β_{fi}^{k} is not equal to 0

The hypothesis for equations (3) is defined as

H_0: $\beta_{s1}^{k} = \beta_{s2i}^{k} = \ldots = \beta_{si}^{k} = 0$
H_1: at least one of the β_{si}^{k} is not equal to 0

The null hypothesis for equations (2) and equations (3) implies that there is no lead-lag relationship between the lagged values of the VOIB between, indicating that information asymmetry spillover does not exist. On the other hand, If the null hypothesis is rejected, it indicates the presence of a lead-lag relationship of the VOIB between markets, implying that one market receives information earlier and subsequently transmits it to another market. The rejection of the null hypothesis provides evidence of information transmission and spillover effects between the markets under study.

In statistical analysis, a one-way relationship refers to a relationship between two variables where the influence flows in only one direction. It means that changes in one variable cause changes in another variable, but the reverse is not true. This relationship is often referred to as unidirectional. Unidirectional relationship of VOIB's spot leads VOIB's future market for investor k require β_{fi}^{k} to be significant and β_{si}^{k} to be insignificant, implying that spot market receives information earlier and subsequently transmits it to future market for investor k. And unidirectional relationship of VOIB's future leads VOIB's spot market for investor k require β_{fi}^{k} to be insignificant and β_{si}^{k} to be significant, implying that future market receives information earlier and subsequently transmits it to spot market for investor k.

The study of Huang, H.-G., et al., (2021) shows that the VOIB of the futures market leads the VOIB of the stock market for foreign investors in Taiwan market, implying that the information asymmetry of foreign investors in the futures market is transmitted to its spot market. However, their findings reveal no similar impacts in the VOIB of local investors and proprietary firms. In addition, they find no evidence that the information asymmetry in stock market leads the information asymmetry in futures market for any particular type of investor. These findings give support to past studies indicating that futures markets tend to lead spot markets in various ways and indicate the information asymmetry in trading caused by types of investors can have spillover effects from the futures market to the spot market. In this study, the result might be the same as result in Taiwan market, the information asymmetry of foreign investors in the futures market is transmitted to its spot market, because the Thai market and the Taiwan market are both emerging markets with similar features.

4.3 Impulse response function (IRF)

In the Vector autoregression (VAR) models, the impulse response function and Cholesky decomposition are powerful tools used to analyze information asymmetry transmissions between futures and spot markets. These techniques provide insights into the dynamic relationships and causalities among variables in the VAR model, allowing us to understand how shocks in one market affect the behavior of variables in both markets.

The impulse response function measures the response of each variable to a one-unit shock in a specific variable while holding all other variables constant. In the context of information asymmetry transmissions, it helps determine the magnitude, duration, and timing of the impact between futures and spot markets. By examining the impulse response function, we can observe the movement of information, the speed of transmission, and any asymmetries that may exist.

Cholesky decomposition is a matrix decomposition technique commonly used in VAR models to identify the causal ordering among variables. It rearranges the variables in the VAR model in a way that captures the cause-and-effect relationships, allowing for a more accurate estimation of the impulse response function. By applying Cholesky decomposition, we can establish an ordered sequence of variables that determines the sequence in which shocks are transmitted through the system. To analyze information asymmetry transmissions between futures and spot markets using a VAR model, we typically employ Cholesky decomposition to establish the causal order. They identify a variable that represents information shocks or asymmetry and place it first in the ordering. The remaining variables are then arranged based on their dependence on the initial shock variable. This causal ordering enables us to accurately estimate the impulse response function and uncover the transmission mechanisms between the two markets.

When studying information asymmetry transmissions between futures and spot markets, we may choose to place the future markets equations first in the ordering due to their potential impact on the entire system before affecting spot market variables (Ameur, 2022). By prioritizing future markets equations at the beginning of the Cholesky decomposition ordering, we aim to capture the notion that shocks or information asymmetry originating in the futures market can have broader implications for the entire system. This method takes into account the fact that changes or events in futures markets can have a wider effect on factors on spot markets. Placing future markets equations first in the Cholesky decomposition ordering reflects the understanding that futures markets often reflect expectations or predictions about future spot market behavior.

In the context of analyzing information asymmetry transmissions and the influence of different investor types on financial markets, we may be prioritized the equations representing local investors at the beginning of the Cholesky decomposition ordering. Placing the equations of local investors first in the ordering acknowledges the potential impact they have on the entire financial market system (Sukmadilaga, 2023). Following the equations of local investors, the Cholesky decomposition ordering can then proceed to the equations representing local institutional investors and foreign investors. This order recognizes that local institutional investors, such as large financial institutions or funds, play an important role in shaping market dynamics. Their actions and decisions can have substantial impacts on market prices, liquidity, and overall sentiment. Similarly, foreign investors often bring in external information, global trends, and unique perspectives.

By combining the impulse response function and Cholesky decomposition within the VAR model framework, we gain a comprehensive understanding of information asymmetry transmissions. They can determine the causal relationships, quantify the impact of shocks, and assess the speed and persistence of information transmission between futures and spot markets.

4.3 Variance decomposition (VDC)

Variance decomposition is a statistical technique used to analyze the sources of variability within a dataset. By conducting variance decomposition in the context of information asymmetry transmissions between futures and spot markets, we can gain valuable insights into the dynamics of information flow and its impact on market efficiency. It allows us to understand the relative importance of each market (futures and spot) in terms of their contribution to the overall variance in asset prices.

Moreover, variance decomposition sheds light on the effectiveness of information transmission mechanisms between futures and spot markets. It helps to determine how much of the total variance can be attributed to the cross-market transmission of information, which is crucial for evaluating the efficiency of these markets and identifying potential areas for improvement.

By quantifying the contributions of different factors and understanding the interplay between futures and spot markets in terms of information asymmetry, variance decomposition provides market participants and regulators with valuable insights. It enables them to develop strategies and interventions that can enhance market efficiency, reduce information asymmetry, and promote fairer and more transparent trading environments. Finally, variance decomposition serves as a valuable analytical tool in understanding the complexities of information asymmetry transmissions between futures and spot markets and making informed decisions to improve market dynamics.

5. Empirical Results

5.1 The unit root test

In our effort to understand the relationship between the volatility of order imbalance (VOIB) in the spot and future markets for each investor type, we began our analysis with stationarity tests. We proceeded with a unit root analysis using the Augmented Dickey-Fuller (ADF) test, incorporating both an intercept and a trend component. Our benchmark for assessing the stationarity of the data was by comparing the ADF statistic with the critical values at both 1% and 5% significance levels. A result where the ADF statistic exceeds the critical value is indicative of the data being stationary. Table 3 shows the unit root test using ADF with the volatility of order imbalance (VOIB) in the spot and future markets for each investor type. All the VOIB appeared to be stationary at the 1% significance level across all periods. This result can reject the null hypothesis of a unit root and conclude that all VOIB indices are stationary.

Additionally, it is essential to ensure that all variables in our model are stationary, not just the endogenous variable. Therefore, we also conducted a unit root analysis incorporating exogenous variables, which are return, illiquidity, trading volume, and the standard deviation in the market returns. This step is important to ensure the robustness of our model. And we found that all these exogenous variables are also stationary at the 1% level, improving the reliability of our research model. In conclusion, based on our analyses, we can confidently state that all variables in our model are stationary.

Table 3: The result of unit root test using Augmented Dickey-Fuller (ADF) test using the following equation: (1): $\Delta Y_{t,k} = \beta_0 + \beta_1 t + \gamma Y_{t-1,k} + \sum_{i=1}^{n} \beta_i Y_{t-i,k} + \varepsilon_t$ (where $Y_{t,k}$ is the volatility of order imbalance (VOIB) at time t of trader group k, β_0 is the intercept term or constant in the regression equation, β_1 is a coefficient for the linear trend in the data over time, γ is the coefficient presenting process root, n is the lag order of the first-differences autoregressive process). γ indicates that the data is a non-stationary time series if γ = 0. In contrast, the series is stationary if γ < 0. The t-values are provided in parentheses below the estimates, indicating the level of significance. *** indicates 1 percent significant level ** indicates 5 percent significant level * indicates 10 percent significant level

Variables	Augmented Dickey-Fuller test: Level
$VOIB_{FI,Stk}$	-1.0220 (-8.90)***
$VOIB_{LS,Stk}$	-0.7478 (-6.58)***
$VOIB_{LI,Stk}$	-0.8215 (-7.12)***
$VOIB_{FI,Fut}$	-0.3966 (-4.29)***
$VOIB_{LS,Fut}$	-0.8408 (-7.35)***
$VOIB_{LI,Fut}$	-0.8252 (-7.32)***

5.2 Vector autoregression (VAR) models

This section will analyze the relationship between variables using the Vector autoregressive (VAR) model, which requires a level of stationarity. The stationarity of the variables presented in the previous section takes importance in this context. Before estimating the vector autoregressive (VAR) model, an initial analysis was conducted to determine the appropriate lag length by applying the Akaike's information criterion (AIC). Based on the criterion, the optimal lag length selected for the VAR estimation for the entire sample is one.

The VAR model in this paper is divided into two sections. The first section constructed a model that mainly considers endogenous variables. The analysis of the VOIB between the futures market and the stock market that only considered endogenous variables is presented in Tables 4, Panel A (using t-tests) and Panel B (using F-tests).

Table 4: The result of the Vector Autoregressive (VAR) result of VOIB using the following equations (2): $VOIB_{t,k,Fut} = \propto_1 + \sum_{i=1}^{l} \alpha_{fi}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \beta_{fi}^{k} VOIB_{t-i,k,Stk} + \varepsilon_{t,k,Fut}$ and equation (3): $VOIB_{t,k,Stk} = \propto_2 + \sum_{i=1}^{l} \alpha_{si}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \beta_{si}^{k} VOIB_{t-i,k,Fut} + \varepsilon_{t,k,Stk}$. The variables included in the table are the monthly of volatility of order imbalance ($\boldsymbol{VOIB_{t,k,Fut}}$), K is the types of investors, which are foreign investors (FI), Local Institutions (LS), and Local investors (LI). The t-values are provided in parentheses below the estimates in Panel A and F-values are provided in Panel B, indicating the level of significance. *** indicates 1 percent significant level ** indicates 5 percent significant level * indicates 10 percent significant level.

Panel A: The result of the T-test for the Vector Autoregressive (VAR) model for endogenous variables.

Variables	Constant	$VOIB_{FI,Stk}$	$VOIB_{LS,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{FI,Fut}$	$VOIB_{LS,Fut}$	$VOIB_{LI,Fut}$
$VOIB_{FI,Stk}$ (-1)	0.0117 (2.20)**	-0.0146 (-0.12)	-1.3823 (-0.28)	-0.2924 (-1.26)	-0.0714 (-0.13)	0.2092 (0.47)	0.1606 (0.47)
$VOIB_{LS,Stk}$ (-1)	0.0255 (1.18)	0.0283 (1.26)	0.6266 (6.91)***	-0.0738 (-1.71)*	-0.0800 (-0.77)	0.2320 (2.81)***	0.144 (2.27)**
$VOIB_{LI,Stk}$ (-1)	0.0116 (1.13)	-0.086 (-1.64)	0.4082 (1.93)*	0.1580 (1.57)	-0.3163 (-1.3)	-0.4477 (-2.33)**	-0.2107 (-1.43)
$VOIB_{FI,Fut}$ (-1)	0.0797 (3.22)***	0.0232 (0.9)	-0.1771 (-1.7)*	-0.1095 (-2.2)**	0.5842 (4.87)***	0.0728 (0.77)	0.0723 (0.99)
$VOIB_{LS,Fut}$ (-1)	0.055 (2.80)***	0.0916 (1.45)	0.0860 (1.73)*	-0.0395 (-0.33)	-0.0719 (-0.25)	0.0630 (0.27)	-0.1554 (-0.87)
$VOIB_{LI,Fut}$ (-1)	0.0492 (3.27)***	-0.1173 (-1.34)	0.1157 (0.33)	0.5191 (3.08)***	-0.0547 (-0.13)	0.1487 (0.46)	0.3174 (1.28)

Panel B: The result of the F-test for the Vector Autoregressive (VAR) model for endogenous variables.

Variables	$VOIB_{FI,Stk}$	$VOIB_{LS,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{FI,Fut}$	$VOIB_{LS,Fut}$	$VOIB_{LI,Fut}$
$VOIB_{FI,Stk}$	-	0.0811	1.593	0.0163	0.2233	0.2238
$VOIB_{LS,Stk}$	1.5828	-	2.9083*	0.5871	7.8751***	5.1518**
$VOIB_{LI,Stk}$	2.7044	3.739*	-	1.6932	5.4139**	2.0361
$VOIB_{FI,Fut}$	0.8045	2.8856*	4.846**	-	0.5871	0.9822
$VOIB_{LS,Fut}$	2.1146	1.0556*	0.1057	0.0603	-	0.7638
$VOIB_{LI,Fut}$	1.7954	0.1072	9.4812***	0.0181	0.213	-

And the VAR model in the second section will be included exogenous in the model. By including exogenous variables, we can improve the model's capacity for explanation, improve its predictive ability, and provide a more comprehensive understanding of the results. This ensures that our analysis considers all relevant factors and provides a more accurate representation of the relationships in the actual world that we are studying. The analysis of the VOIB between the futures market and the stock market, considering both endogenous and exogenous variables, is presented in Tables 5, Panel A (using t-tests) and Panel B (using F-tests).

Table 5: The result of the Vector Autoregressive (VAR) result of VOIB using the following equations (4): $VOIB_{t,k,Fut} = \propto_3 + \sum_{i=1}^{l} \alpha_{fi}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \beta_{fi}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \gamma_{fi}^{ret}\, Ret_{t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{vol}\, \Delta \mathrm{Vol}_{t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{IIliq}\, IIliq_{\,t-i,Fut} + \sum_{i=1}^{l} \gamma_{fi}^{SDRet}\, SDRet_{t-i,Fut} + \varepsilon_{t,k,Fut}$ and (5): $VOIB_{t,k,Stk} = \propto_4 + \sum_{i=1}^{l} \alpha_{si}^{k} VOIB_{t-i,k,Stk} + \sum_{i=1}^{l} \beta_{si}^{k} VOIB_{t-i,k,Fut} + \sum_{i=1}^{l} \gamma_{f=si}^{ret}\, Ret_{t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{vol}\, \Delta \mathrm{Vol}_{t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{IIliq}\, IIliq_{\,t-i,Stk} + \sum_{i=1}^{l} \gamma_{si}^{SDRet}\, SDRet_{t-i,Stk} + \varepsilon_{t,k,Stk}$. The variables included in the table are the monthly of volatility of order imbalance (**$VOIB_{t,k,Fut}$**), K is the types of investors, which are foreign investors (FI), Local Institutions (LS), and Local investors (LI). The table also considers exogenous variables such as monthly return (Ret), monthly change in total trading volume (ΔVol), market illiquidity (Illiq), and standard deviation in market returns (SDRet). The t-values are provided in parentheses below the estimates in Panel A and F-values are provided in Panel B, indicating the level of significance. *** indicates 1 percent significant level ** indicates 5 percent significant level * indicates 10 percent significant level.

Panel A: The result of the T-test for the Vector Autoregressive (VAR) model for both endogenous and exogenous variables.

Variables	Constant	$VOIB_{FI,Stk}$	$VOIB_{LS,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{FI,Fut}$	$VOIB_{LS,Fut}$	$VOIB_{LI,Fut}$
$VOIB_{FI,Stk}$ (-1)	0.013 (2.32)**	0.0114 (0.09)	-0.3236 (-0.66)	-0.2937 (-1.26)	0.1716 (0.35)	0.3137 (0.76)	0.1606 (0.50)
$VOIB_{LS,Stk}$ (-1)	0.0107 (0.5)	0.0252 (0.99)	0.6891 (7.10)***	-0.037 (-0.8)	-0.1301 (-1.34)	0.0916 (1.53)	0.0866 (1.27)
$VOIB_{LI,Stk}$ (-1)	0.0054 (0.53)	-0.089 (-1.57)	0.4152 (1.9)*	0.1188 (1.15)	-0.1790 (-0.82)	-0.0719 (-0.26)	-0.2107 (-1.5)
$VOIB_{FI,Fut}$ (-1)	0.0963 (4.50)***	0.0047 (0.15)	-0.081 (-0.70)	-0.0314 (-0.57)	0.4471 (3.85)***	-0.0178 (-0.18)	0.0723 (1.04)
$VOIB_{LS,Fut}$ (-1)	0.0705 (3.93)***	0.0752 (1.06)	0.5386 (1.99)**	0.0085 (0.07)	-0.2997 (-1.1)	-0.0719 (-0.26)	-0.1554 (-0.92)
$VOIB_{LI,Fut}$ (-1)	0.0607 (4.02)***	-0.0976 (-1.04)	-0.1524 (-0.43)	0.434 (2.6)***	0.1915 (0.53)	0.2549 (0.85)	0.3174 (1.35)

Panel B: The result of the F-test for the Vector Autoregressive (VAR) model for both endogenous and exogenous variables.

Variables	$VOIB_{FI,Stk}$	$VOIB_{LS,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{FI,Fut}$	$VOIB_{LS,Fut}$	$VOIB_{LI,Fut}$
$VOIB_{FI,Stk}$	-	0.4307	1.5875	0.1204	0.5802	0.3089
$VOIB_{LS,Stk}$	0.9589	-	0.6439	1.7874	0.0463	1.6086
$VOIB_{LI,Stk}$	2.4649	3.6032*	-	0.6653	0.6475	0.9161
$VOIB_{FI,Fut}$	0.0238	0.4885	0.3291	-	0.0337	0.0479
$VOIB_{LS,Fut}$	1.1286	3.9609**	0.0044	1.2188	-	2.4652
$VOIB_{LI,Fut}$	1.0841	0.1809	6.7446***	0.2838	0.725	-

As shown in Tables 4 and 5, null hypothesis is rejected, it implies the presence of significant relationships of VOIB between markets.

A significant difference becomes clear after comparing both sections. The relationships that showed significant coefficients at a lag of 1 in the first section became weaker in the second section. For example, in the first section that considered only endogenous variables, the relationship coefficient of $VOIB_{LS,Stk}$ to $VOIB_{LI,Fut}$ and the relationship coefficient of $VOIB_{LB,Stk}$ to $VOIB_{LB,Fut}$ is found to be positive and marginal significant at the level of 10%. While it does not show the significant level in the second section that considered both endogenous and exogenous variables. This weakening of significance could possibly be related to the second section's improved variable control. In the second section of the previous example, the significance is weakened because the control variables in the second section were able to capture and explain the significant result in the first section.

There are three relationships that the coefficients statistically significant at lag 1 in both sections. Based on the results presented in tables 4 and 5, (i) the relationship coefficient of $VOIB_{LI,Stk}$ to $VOIB_{LB,Stk}$ and (ii) the relationship coefficient of $VOIB_{LB,Fut}$ to $VOIB_{LB,Stk}$ are found to be positive and marginally significant at the 10% and 5% level. Furthermore, (iii) the relationship coefficient of $VOIB_{LI,Fut}$ to $VOIB_{LI,Stk}$ is found to be positive and significant at the 1% level.

The results indicate that informed investors exist, and that information is transmitted between different investor types and markets. The results (i) suggested that local investors have a higher level of information compared to other types of investors. They are informed investors and are able to obtain information in advance and transmit this information to local institutions in the spot market. The findings of Tanthanongsakkun (2018) study support the notion that local investors are more likely to have information. The researchers found that the Stock Exchange of Thailand (SET) shows a significant presence of local investors, and the trading activities of these investors are correlated with stock returns. The researchers also found that trading by local investors has the most significant influence and impact volatility in Thai market. Local investors are also the primary drivers of price discovery in market, according to Hultman et al. (2020). Local institutions have increasingly found value in monitoring and interpreting the actions of local investors, aiming to derive insights that might not be readily apparent through traditional channels. Behavioral Analysis, a field that delves deep into the psychological underpinnings of investment decisions, suggests that local investors can often exhibit patterns such as herding behavior, overreactions to news, and other anomalies driven by cognitive biases, Barberis et al.(2002). By studying these behaviors, institutions can gain a clearer understanding of market sentiment and potential market movements. In parallel, local investors play an essential role in providing liquidity. Their cumulative trading volumes, especially in less frequently traded assets, assist in price discovery and offer a semblance of market stability. Institutions, by analyzing these trading patterns, can strategize their trades more efficiently to minimize price impacts, capitalizing on the liquidity provisions offered by the local segment, Ivković et al.(2005). The connection between institutional and local investors in contemporary financial ecosystems is highlighted by such indirect information routes.

(ii) Local institutions showed their informed investor behavior by primarily adjusting their trading activities in the future market. Subsequently, they transfer that information and proceed to change their trading activities in the spot markets. (iii) Local investors showed a higher level of information asymmetry, as they primarily adjust their trading activities in the futures market before afterwards transferring this information to change their trading activities in the spot markets.

Overall, local institutions and local investors are indicated as informed investors in this study. The results of this study provide empirical evidence in support of the hypothesis that there are investors who have information and are considered to be informed investors. These findings presented here align with the research conducted by Boonvorachote et al. (2012), who examined the trading behaviors of various investor types on the Stock Exchange of Thailand (SET). Their research indicated that Thai investors, local institutions and local investors, show characteristics of informed investors and they tend to enjoy superior information over foreign traders. Moreover, the study of Chen (2020) also found trading of local investors is informative around the world.

The results of this study also provide empirical evidence in support of the hypothesis that investors tend to adjust their trading activities in the futures market prior to making adjustments in the spot market. These findings presented here align with the research conducted by Bamrungsap (2018), who found that informed investors often prefer to adjust their trading in the futures market before the spot market. Futures markets provide greater liquidity, enabling traders to take exit positions without inducing substantial price shifts. This is complemented by the benefit of leverage in futures contracts, which permits traders to manage larger positions with the same capital compared to spot markets. The futures market frequently serves as a primary arena for price discovery, meaning that new information tends to be integrated into futures prices before being reflected in spot prices. Some investors might also find the transaction costs in futures trading to be comparatively lower, so trading in the futures market can signal potential movements and influence spot market trading. Additionally, the futures market offers traders opportunities to hedge their spot market exposures, ensuring risk is managed effectively.

However, the results of this study are inconsistent with the previous research conducted by Huang, H.-G., et al. (2021). It has been shown that foreign investors in the Taiwanese market have a higher level of information, and they transmit this information from futures markets to spot markets. The contrasting findings between the Taiwanese and Thai markets can be attributed to the different type of investors in each market. The Taiwanese market is dominated by foreign investors, whereas the Thai market is dominated by local investors. When examining different markets, we frequently found some investors are more active than others. The most active type of investor typically has the inside information. Consequently, they are usually considered as informed investors. The results of this study are consistent with the previous research conducted by Huang, H.-G., et al. (2021) which provides empirical evidence of the notion that information primarily transmits from future markets to spot markets. Curiously, they also observed a lack of information transfer from spot markets to future markets. This consistent pattern across studies highlights the different information relationships between these two market varieties.

5.3 Impulse response function (IRF)

In our study utilizing the Vector autoregression (VAR) models, our aim is to understand the transfer of information between futures and spot markets. In this section, we employ two primary techniques, the impulse response function and the Cholesky decomposition. These approaches are instrumental in helping us understand how unexpected changes or 'shocks' in one market impact on another market. While the previously section, we focus on how the effects of 'VOIB' in one market impact in another. Residual one standard deviation is used as a method for decomposition setting the impulses to one standard deviation of the residuals.

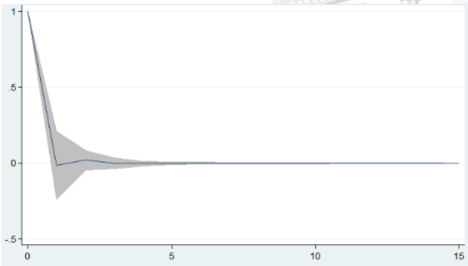
An essential component of our methodology is the Cholesky decomposition. In this approach, we've prioritized local investors by positioning them at the beginning. The rationale behind this arrangement is grounded in research, specifically findings by Tanthanongsakkun (2018), which highlight the significant role local investors play in shaping financial markets. By placing them at the beginning, we aim to gain a clearer insight into their influence on market dynamics. Following the equations of local investors, the Cholesky decomposition ordering can then proceed to the equations representing local institutional investors and foreign investors.

The results from the Impulse Response Function all over different periods are presented in Figure 2. The results depicted in Panel A shed light on the nuanced reactions to shocks across these markets when the agent in question is a foreign investor.

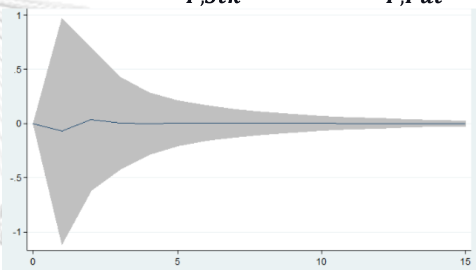
An observation is that shocks in the $VOIB_{F,Stk}$ seem to carry implications for the $VOIB_{F,Fut}$ landscape and vice versa. Response from $VOIB_{F,Stk}$ to $VOIB_{F,Fut}$, A preliminary examination hints at a somewhat intricate relationship. Specifically, an impulse in $VOIB_{F,Stk}$ propagates a negative marginal influence on $VOIB_{F,Fut}$ for the initial 2 lags post-shock. This adverse effect doesn't wane immediately; it lingers, exerting a negative marginal influence up to the 4th lag. It is essential to interpret this with caution, as it suggests that disturbances in the stock market order imbalance will reverse in the futures market in a counter-directional manner, at least in the short run. Response from $VOIB_{F,Fut}$ to $VOIB_{F,Stk}$, it disperses a positive marginal influence over the stock market order imbalance, $VOIB_{F,Stk}$, spanning up to the fourth lag. This observation underscores a more harmonious transmission mechanism wherein perturbations in the futures market order imbalances accentuate similar directional shifts in the stock market for foreign investors.

Figure 2: Impulse response function

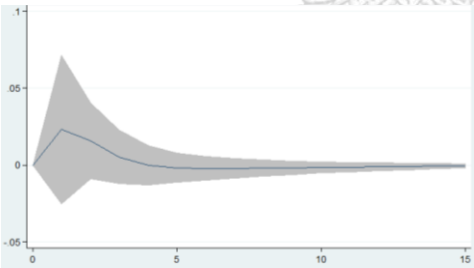
Panel A. Impulse response function between $\boldsymbol{VOIB_{F,Stk}}$ and $\boldsymbol{VOIB_{F,Fut}}$



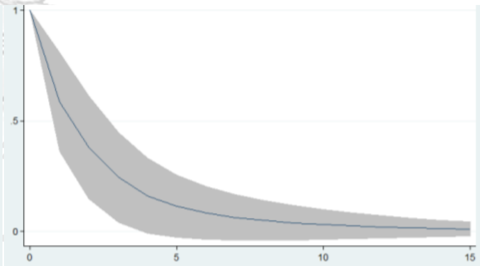
Response of $\boldsymbol{VOIB_{F,Stk}}$ to $\boldsymbol{VOIB_{F,Stk}}$



Response of $\boldsymbol{VOIB_{F,Stk}}$ to $\boldsymbol{VOIB_{F,Fut}}$



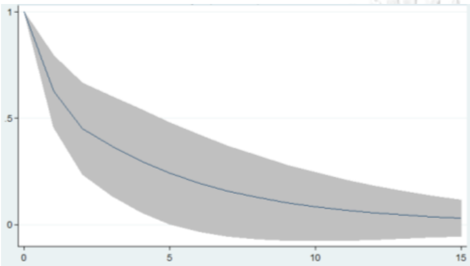
Response of $\boldsymbol{VOIB_{F,Fut}}$ to $\boldsymbol{VOIB_{F,Stk}}$



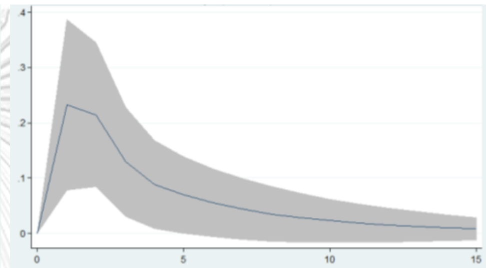
Response of $\boldsymbol{VOIB_{F,Fut}}$ to $\boldsymbol{VOIB_{F,Fut}}$

Panel B, we found a clear pattern became evident in Panel B with local institutions, changes in $\mathrm{VOIB_{LB,Fut}}$ result in a significant increase in $\mathrm{VOIB_{LB,Stk}}$. Changes in the futures market order imbalance, $VOIB_{LB,Fut}$, are connected to important implications in the stock market and, $VOIB_{LB,Stk}$. The available evidence implies a strong interconnection between these markets, indicating that the operations of local institutions in one market cannot be adequately understood without considering their relationship to the other market. The implications for the stock market. Response from $VOIB_{LB,Stk}$ to $VOIB_{LB,Fut}$, a natural fluctuation originating from the disparity in stock market orders, $VOIB_{LB,Stk}$, exerts a palpable positive influence on its futures counterpart, $VOIB_{LB,Fut}$, and this influence persists up to 4 lags. This finding emphasizes the influential role the stock market plays in dictating the directional thrust of the futures market when it comes to local institutional activities. Response from $VOIB_{LB,Fut}$ to $VOIB_{LB,Stk}$, in a similar, $VOIB_{LB,Stk}$, till the fourth lag. This shows that the two markets work well together in both directions. When there are problems in the futures market, local businesses see consistent changes in the direction of the stock market. This finding is consistent with what we found earlier in the Vector autoregression (VAR) section, specifically results (ii), which indicate that local institutions in future market have a marginal impact on local institutions in spot market. The alignment seen between the results obtained from this panel presented strong empirical support for the results from the previous section and our hypothesis, which indicate the existence of a positive transference effect from the futures market to the spot market.

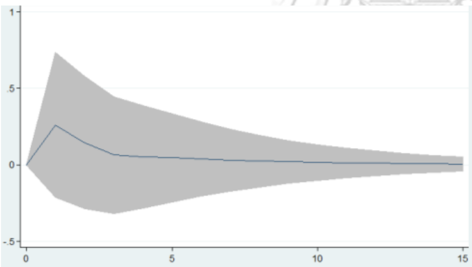
Panel B. Impulse response function between $\boldsymbol{VOIB_{LB,Stk}}$ and $\boldsymbol{VOIB_{LB,Fut}}$



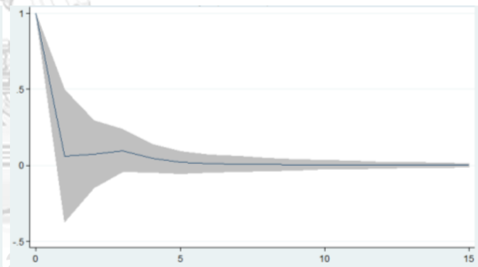
Response of $\boldsymbol{VOIB_{LB,Stk}}$ to $\boldsymbol{VOIB_{LB,Stk}}$



Response of $\boldsymbol{VOIB_{LB,Stk}}$ to $\boldsymbol{VOIB_{LB,Fut}}$



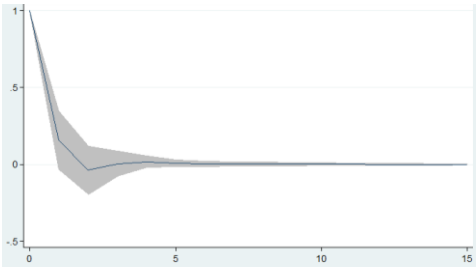
Response of $\boldsymbol{VOIB_{LB,Fut}}$ to $\boldsymbol{VOIB_{LB,Stk}}$



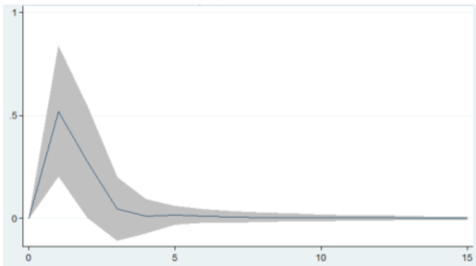
Response of $\boldsymbol{VOIB_{LB,Fut}}$ to $\boldsymbol{VOIB_{LB,Fut}}$

In Panel C, the spotlight shifts to local investors, revealing the intricacies between the volatility of order imbalances in the stock and futures markets. Panel C mirrors the findings from Panel B, albeit with nuanced distinctions catered to local investors. It shows how changes in one market have different effects on the other. Response from $VOIB_{LI,Stk}$ to $VOIB_{LI,Fut}$, Observing local investors' reaction to stock market imbalances reveals a remarkable pattern. Shocks from $VOIB_{LI,Stk}$. Shocks from $VOIB_{LI,Stk}$ has a positive influence on $VOIB_{LI,Fut}$, holding its ground consistently for up to 4 lags. This observation intimates that local investors' activities in the stock market can often act as a leading indicator, precipitating directional shifts in the futures market. Response from $VOIB_{LI,Fut}$ to $VOIB_{LI,Stk}$, contrasting the previous dynamic, shocks stemming from the futures market, $VOIB_{LI,Fut}$, translate to a negative influence on the stock market order imbalance, $VOIB_{LI,Stk}$, up to the fourth lag. This suggests that any significant activity by local investors in the futures market tends to oppose the concurrent trends in the stock market.

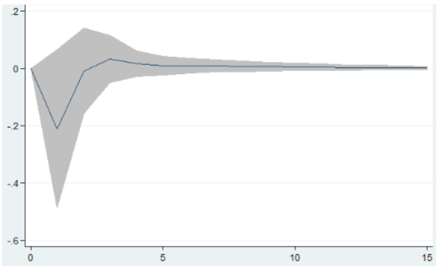
Panel C. Impulse response function between $\boldsymbol{VOIB_{LI,Stk}}$ and $\boldsymbol{VOIB_{LI,Fut}}$



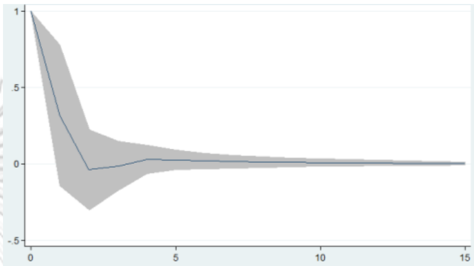
Response of $\boldsymbol{VOIB_{LI,Stk}}$ to $\boldsymbol{VOIB_{LI,Stk}}$



Response of $\boldsymbol{VOIB_{LI,Stk}}$ to $\boldsymbol{VOIB_{LI,Fut}}$



Response of $\boldsymbol{VOIB_{LI,Fut}}$ to $\boldsymbol{VOIB_{LI,Stk}}$



Response of $\boldsymbol{VOIB_{LI,Fut}}$ to $\boldsymbol{VOIB_{LI,Fut}}$

5.3 Variance decomposition (VDC)

In this study, we have also employed variance decomposition as a method to analyze and understand the fluctuations in volatility of order imbalance (VOIB) across different markets and types of investors. The technique of variance decomposition offers a comprehensive perspective on the variability observed in our dependent variables. It allows us to understand the percentage of fluctuations that may be attributed to the underlying shocks, as compared to the shocks originating from other variables within the system. This method has shed light on the process in which unexpected shifts or sudden changes in the VOIB of one investor type can spread across markets or among various types of investors.

The results, as detailed in Table 6, showed how different types of investors respond to changes in the VOIB across markets. In every panel of the table, the VOIB of each investor type is impacted primarily by their own shocks rather than those of other investor types.

Panel A, we use VDC to quantify the relative importance of different shocks on the variability of $VOIB_{F,Stk}$.

Table 6: Estimates of Variance Decomposition

Panel A: Variance decomposition on volatility of order imbalance of foreign investors in spot market (**$VOIB_{F,Stk}$**)

	Response of $VOIB_{F,Stk}$ to a shock (or impulse) in						
Lags (n)	**$VOIB_{F,Stk}$**	**$VOIB_{LB,Stk}$**	**$VOIB_{LI,Stk}$**	**$VOIB_{F,Fut}$**	**$VOIB_{LB,Fut}$**	**$VOIB_{LI,Fut}$**	**Total**
1	82.2425%	0.9806%	12.5334%	3.9813%	0.0022%	0.2601%	100.00 %
3	76.1065%	2.5735%	14.1204%	4.7641%	1.4693%	0.9661%	100.00 %
5	75.7368%	2.9484%	14.0544%	4.7603%	1.4837%	1.0164%	100.00 %
7	75.6299%	3.0104%	14.0387%	4.7820%	1.4845%	1.0169%	100.00 %
10	75.5636%	3.0934%	14.0312%	4.8091%	1.4859%	1.0168%	100.00 %
13	75.5431%	3.1055%	14.0289%	4.8194%	1.4864%	1.0168%	100.00 %
15	75.5382%	3.1082%	14.0284%	4.8220%	1.4865%	1.0168%	100.00 %

At a lag of 1, shocks to $VOIB_{F,Stk}$ itself account for most of its fluctuations at 82.2425%. Shocks from $VOIB_{LI,Stk}$ contribute to 12.5334%, while $VOIB_{LB,Stk}$ and $VOIB_{LB,Stk}$ and $VOIB_{F,Fut}$ account for only 0.9806% and 3.9813% respectively. As the number of lags increase, there is a marginal shift in the contribution of each shock towards the variability of $VOIB_{F,Stk}$. By lag 15, the impact of its own shock reduces slightly to 75.5382%, while the contributions from $VOIB_{LB,Stk}$ and $VOIB_{LI,Stk}$ increase to 3.1082% and 14.0284% respectively. The shock from $VOIB_{F,Fut}$ sees an incremental rise, accounting for 4.8220% of the variance by lag 15. The other types, $VOIB_{LB,Fut}$ and $VOIB_{LI,Fut}$, contribute minimally throughout the lags considered, indicating that their shocks have a limited direct influence on the variability of $VOIB_{F,Stk}$ over the short to medium term. In this panel, the VDC analysis shows that the predominant source of variation in $VOIB_{F,Stk}$ over varying lags stems primarily from its own shocks, followed by $VOIB_{LI,Stk}$ The shocks from the other variables play a lesser role in influencing its variance over the time periods considered. This supports the result from the previous, the VAR section, VOIB of local investors influence VOIB of other investors in the market.

Panel B, we focus on $VOIB_{LB,Stk}$. At an initial lag of 1, the shocks to $VOIB_{LB,Stk}$ itself account for a substantial 74.8269% of its fluctuations.

Panel B: Variance decomposition on volatility of order imbalance of local institutions in spot market (**$VOIB_{LB,Stk}$**)

	Response of $VOIB_{LB,Stk}$ to a shock (or impulse) in						
Lags (n)	$VOIB_{F,Stk}$	$VOIB_{LB,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{F,Fut}$	$VOIB_{LB,Fut}$	$VOIB_{LI,Fut}$	**Total**
1	0.0000%	74.8269%	11.5905%	0.4499%	10.8428%	2.2899%	100.00%
3	0.0667%	68.7495%	7.4350%	4.1929%	12.5543%	6.9727%	100.00%
5	0.0957%	65.8455%	6.8550%	4.3429%	16.7659%	6.1088%	100.00%
7	0.0776%	64.6160%	6.6101%	4.4472%	18.4972%	5.7519%	100.00%
10	0.0758%	63.9252%	6.4835%	4.4988%	19.4474%	5.5697%	100.00%
13	0.0747%	63.7235%	6.4474%	4.5138%	19.7229%	5.5178%	100.00%
15	0.0745%	63.6767%	6.4390%	4.5172%	19.7867%	5.5059%	100.00%

The other substantial contributors to its variance are shocks from $VOIB_{LI,Stk}$ and $VOIB_{LB,Fut}$, causing 11.5905% and 10.8428% respectively. The influence of the other variables, particularly $VOIB_{F,Stk}$, is minimal, with it accounting for 0.0000% at the first lag. With the progression in the number of lags, there are noticeable shifts in the contributions. By the 15th lag, although the self-shock to $VOIB_{LB,Stk}$ remains predominant at 63.6767%, its contribution has slightly decreased from the first lag. Concurrently, the influence of shocks from $VOIB_{LB,Fut}$ increases significantly, reaching 19.7867% by the 15th lag. The contribution of $VOIB_{LI,Stk}$ decreases to 6.4390%, and $VOIB_{F,Fut}$ slightly increases to 4.5172%. The shocks from $VOIB_{F,Stk}$ continue to have a very minimal impact on $VOIB_{LB,Stk}$ throughout the lags considered. In summation, the VDC analysis reveals that while the primary source of variability in $VOIB_{LB,Stk}$ stems from its own shocks, there are significant influences, especially from $VOIB_{LB,Fut}$ as the lags increase. Shocks from $VOIB_{F,Stk}$, however, consistently play a negligible role in the variation of $VOIB_{LB,Stk}$ across all considered lags. This finding is consistent with what we found earlier in the Vector autoregression (VAR) section, specifically results (i) and (ii), which indicate that local investors in spot market and local institutions in future market have a marginal impact on local institutions in spot market.

Panel C, we focus on $VOIB_{LI,Stk}$. At a lag of 1, a dominant 98.7760% of the variance in $VOIB_{LI,Stk}$ arises from its own shocks. The remaining contributions are minuscule in comparison, with shocks from $VOIB_{F,Fut}$ contributing 1.0147% and $VOIB_{LI,Fut}$ causing 0.2062%. The impacts from $VOIB_{F,Stk}$, $VOIB_{LB,Stk}$, and $VOIB_{LB,Fut}$ are basically non-existent at this lag, registering 0.0000%, 0.0000%, and 0.0031% respectively.

Panel C: Variance decomposition on volatility of order imbalance of local investors in spot market (**$VOIB_{LI,Stk}$**)

	Response of to $VOIB_{LI,Stk}$ a shock (or impulse) in						
Lags (n)	$VOIB_{F,Stk}$	$VOIB_{LB,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{F,Fut}$	$VOIB_{LB,Fut}$	$VOIB_{LI,Fut}$	**Total**
1	0.0000%	0.0000%	98.7760%	1.0147%	0.0031%	0.2062%	100.00%
3	1.2722%	0.9281%	64.9056%	5.3408%	1.0202%	26.5333%	100.00%
5	1.2785%	1.0549%	64.6320%	5.3959%	1.1960%	26.4426%	100.00%
7	1.2776%	1.0823%	64.5764%	5.4523%	1.1978%	26.4230%	100.00%
10	1.2770%	1.1016%	64.5491%	5.4623%	1.1990%	26.4110%	100.00%
13	1.2769%	1.1074%	64.5413%	5.4676%	1.1993%	26.4076%	100.00%
15	1.2768%	1.1087%	64.5395%	5.4689%	1.1993%	26.4068%	100.00%

However, as the number of lags increases, there is a significant diversification in the contributions. By lag 15, while the self-shock to $VOIB_{LI,Stk}$ remains predominant at 64.5395%, it has significantly decreased from the initial lag. This reduction is counterbalanced, most notably by a substantial rise in the impact from $VOIB_{LI,Fut}$, which accounts for 26.4068% by the 15th lag. There are also modest increases in the contributions of shocks from $VOIB_{F,Stk}$, $VOIB_{LB,Stk}$, $VOIB_{F,Fut}$, and $VOIB_{LB,Fut}$, which register 1.2768%, 1.1087%, 5.4689%, and 1.1993% respectively at the same lag. In conclusion, the VDC analysis from Panel C indicates that while the primary source of variation in $VOIB_{LI,Stk}$ arises from its own shocks, particularly at short lags, the influence of other variables, especially $VOIB_{LI,Fut}$, becomes considerably more pronounced as the lag increases. Panel C found that the shock (or impulse) of $VOIB_{LI,Fut}$ has a significant impact on $VOIB_{LI,Stk}$. This is also consistent with result (iii) from the VAR section, which indicates that local investors in the futures market have a substantial effect on local investors in the spot market.

Panel D, we focus on $\text{VOIB}_{\text{F,Fut}}$. Initially, at a lag of 1, it represented 77.9494% of the variance in $\text{VOIB}_{\text{F,Fut}}$ is attributed to its own shocks.

Panel D: Variance decomposition on volatility of order imbalance of foreign investors in future market (**$VOIB_{F,Fut}$**)

	Response of $VOIB_{F,Fut}$ to a shock (or impulse) in						
Lags (n)	$VOIB_{F,Stk}$	$VOIB_{LB,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{F,Fut}$	$VOIB_{LB,Fut}$	$VOIB_{LI,Fut}$	**Total**
1	0.0000%	0.0000%	0.0000%	77.9494%	0.1534%	21.8972%	100.00%
3	0.0168%	0.6153%	1.8848%	79.8094%	0.1514%	17.5223%	100.00%
5	0.0157%	1.6014%	2.1121%	79.6833%	0.2163%	16.3711%	100.00%
7	0.0155%	2.2626%	2.2018%	79.2426%	0.2626%	16.0148%	100.00%
10	0.0155%	2.6849%	2.2444%	78.9215%	0.2918%	15.8420%	100.00%
13	0.0155%	2.8160%	2.2561%	78.8180%	0.3007%	15.7938%	100.00%
15	0.0155%	2.8468%	2.2588%	78.7934%	0.3027%	15.7827%	100.00%

Another significant contribution comes from $VOIB_{LI,Fut}$ at 21.8972%. The influence of the remaining variables, specifically $VOIB_{F,Stk}$, $VOIB_{LB,Stk}$, $VOIB_{LI,Stk}$, and $VOIB_{LB,Fut}$ is almost negligible, with them accounting for 0.0000%, 0.0000%, 0.0000%, and 0.1534% respectively. $VOIB_{F,Fut}$ slightly decreases to 78.7934%. Concurrently, there is an increase in contributions from $VOIB_{LB,Stk}$ and $VOIB_{LI,Stk}$ which rise to 2.8468% and 2.2588% respectively. The contribution of $VOIB_{LI,Fut}$ decreases to 15.7827%. The shocks from $VOIB_{F,Stk}$ and $VOIB_{LB,Fut}$ maintain a low influence across all the considered lags.

Panel E, we focus on $VOIB_{LB,Fut}$. At the outset, at lag 1, a predominant 75.5914% of the variance in $VOIB_{LB,Fut}$ can be attributed to its own shocks.

Panel E: Variance decomposition on volatility of order imbalance of local institutions in future market (**$VOIB_{LB,Fut}$**)

	Response of to $VOIB_{LB,Fut}$ a shock (or impulse) in						
Lags (n)	**$VOIB_{F,Stk}$**	**$VOIB_{LB,Stk}$**	**$VOIB_{LI,Stk}$**	**$VOIB_{F,Fut}$**	**$VOIB_{LB,Fut}$**	**$VOIB_{LI,Fut}$**	**Total**
1	0.0000%	0.0000%	0.0000%	0.0000%	75.5914%	24.4086%	100.00%
3	0.3120%	7.3654%	3.2884%	0.7661%	66.9071%	21.3609%	100.00%
5	0.3118%	9.0642%	3.3348%	0.9320%	65.4693%	20.8880%	100.00%
7	0.3089%	9.5623%	3.3441%	1.2089%	64.8557%	20.7199%	100.00%
10	0.3073%	9.7977%	3.3576%	1.4270%	64.4903%	20.6201%	100.00%
13	0.3068%	9.8612%	3.3619%	1.5002%	64.3800%	20.5899%	100.00%
15	0.3066%	9.8757%	3.3629%	1.5178%	64.3542%	20.5828%	100.00%

Additionally, $VOIB_{LI,Fut}$ offers a substantial contribution of 24.4086%. The influences from other variables like $VOIB_{F,Stk}$, $VOIB_{LB,Stk}$, $VOIB_{LI,Stk}$ and $VOIB_{F,Fut}$ are non-existent at this lag, accounting for 0.0000% each. Moving to higher lags, there is an evident shift in these proportions. By lag 15, the self-shock to $VOIB_{LB,Fut}$ declines to 64.3542%. Simultaneously, there are rising contributions from $VOIB_{LB,Stk}$ and $VOIB_{LI,Stk}$, which amount to 9.8757% and 3.3629% respectively. The influence from $VOIB_{F,Stk}$ remains low at 0.3066%, while $VOIB_{F,Fut}$ grows marginally to 1.5178%. The contribution of $VOIB_{LI,Fut}$, although declining, stays significant at 20.5828%.

Panel F, Variance Decomposition (VDC) illustrates the contributions of different variables to the variability in the order imbalance of local investors in the future market, denoted as $VOIB_{LI,Fut}$. Starting with lag 1, we notice a stark and straightforward situation: $VOIB_{LI,Fut}$ is entirely driven by its own shocks, accounting for a full 100.0000% of the variance. All other variables have no influence at this lag. However, as we progress to longer lags, the picture becomes more complex. By lag 15: The self-shock's contribution to $VOIB_{LI,Fut}$ decreases to 88.7054%. $VOIB_{LB,Stk}$ becomes a significant source of variability, contributing 5.4471%. $VOIB_{LI,Stk}$ offers a smaller yet notable contribution of 1.1469%. $VOIB_{F,Stk}$ and $VOIB_{F,Fut}$ show minor influences at 0.2640% and 1.4207%, respectively. $VOIB_{LB,Fut}$ also exerts some influence with a contribution of 3.0159%. In essence, the VDC in Panel F showcases that while the volatility in the order imbalance of local investors in the future market is primarily driven by its own shocks, external influences, especially from $VOIB_{LB,Stk}$ and to a lesser extent from other variables, start to play a role as we consider longer lags.

Panel F: Variance decomposition on volatility of order imbalance of local investors in future market (**$VOIB_{LI,Fut}$**)

	Response of $VOIB_{LI,Fut}$ to a shock (or impulse) in						
Lags (n)	$VOIB_{F,Stk}$	$VOIB_{LB,Stk}$	$VOIB_{LI,Stk}$	$VOIB_{F,Fut}$	$VOIB_{LB,Fut}$	$VOIB_{LI,Fut}$	**Total**
1	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	100.00%
3	0.2610%	4.3494%	1.0612%	1.1950%	3.0238%	90.1096%	100.00%
5	0.2657%	5.0915%	1.1218%	1.2238%	3.0080%	89.2892%	100.00%
7	0.2647%	5.3118%	1.1332%	1.3082%	3.0149%	88.9673%	100.00%
10	0.2642%	5.4135%	1.1431%	1.3864%	3.0158%	88.7770%	100.00%
13	0.2640%	5.4409%	1.1462%	1.4140%	3.0159%	88.7190%	100.00%
15	0.2640%	5.4471%	1.1469%	1.4207%	3.0159%	88.7054%	100.00%

6. Conclusion

The concept of volatility of order imbalance (VOIB), as developed by Chordia et al. (2019), serves as a newly developed proxy measure to measure information asymmetry. This study specifically highlights its implementation within the Thailand Futures Exchange (TFEX) and the Stock Exchange of Thailand (SET). The primary objective of this study was to understand the background and transmission of private information inside these markets, thereby providing insights into the potential information risks that different investors might face. In this study, we provide further evidence of the relationship between VOIB. The VOIB was constructed from a unique account-level transaction dataset containing complete trading records of futures and spot markets for different types of investors from January 2017 to December 2022. Our dataset enables us to identify the trading activities conducted by various types of investors, including Foreign Investors (FI), Local Institutions (LS), and Local Investors (LI).

Given Huang, H.-G., et al.'s (2021) found of VOIB relationships in the Taiwan market, we provided further evidence of VOIB relationships in Thailand. Vector autoregression (VAR) is employed in this study to analyze the relationship between VOIB in the futures and stock markets.

The VAR model is divided into two sections, the first section focuses mainly on endogenous variables, while the second section includes exogenous variables. The findings of our study indicated that among all three types of investors in Thailand, the trading behaviors of local institutional and local investors showed relationship with information compared to foreign investors. This suggests that local institutional and local investors are more likely to have informed investor behaviors. Our study revealed that local investors have the ability to acquire information beforehand and afterwards transmit this information to local institutions in the spot market. The study conducted by Tanthanongsakkun (2018) provided empirical evidence that trading activity by local investors showed significant impact on the volatility in Thai market. According to

Hultman et al. (2020), local investors also play an important part in driving price discovery. Additionally, our study indicated that the VOIB in the futures market showed an important impact on the VOIB in the stock market, including among local institutional and local investors. This finding suggested that the information from local institutional and local investors in the futures market is effectively transmitted to the spot market. The implications of our findings align with the research conducted by Boonvorachote et al. (2012) and Chen (2020), which examined the trading habits of different investor types on SET. The findings of their study suggested that Thai investors, local institutions, and local investors showed behaviors of informed investors, hence benefiting from a comparative advantage in terms of information access compared to foreign investors.

Moreover, this study employed impulse response functions and variance decomposition techniques to analyze the effects caused by shocks in VOIB. The findings of this study provided empirical support for our hypotheses, which implied the existence of informed traders who have information and investors tend to adjust their trading activities in the futures market prior to making adjustments in the spot markets.

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