International Journal of Business and Society, Vol. 25 No. 2, 2024, 773-788

INTRADAY RETURN OF WINNERS VS LOSERS: INDONESIAN CAPITAL MARKET EVIDENCE

Masyhuri Hamidi ♣
Universitas Andalas

Fajri Adrianto
Universitas Andalas

Nanda Nanda
Universitas Baiturrahmah

Eko Dwi Putra
Universitas Metamedia

Amer Azlan Abdul Jamal
Universiti Malaysia Sabah

ABSTRACT

The aim of this study is to determine intraday returns in the Indonesian capital market, using sample of 177 listed Indonesian companies from 2021-2022. This study adopts a multiple linear regression analysis, where the return of the last half hour as an endogenous variable consists of winners and losers, the return of the first half hour of trading, the volume of the first half hour, overnight returns, and the USA index futures as an exogenous variable. The originality of this research aims to demonstrate empirical evidence on intraday returns by distinguishing winner & loser stocks and the relationship between the intraday returns of winners and losers with volume, overnight, and US index futures in the emerging market (Indonesia). We find that the first half hour of trading can impact future return. The return of the first thirty minutes is significantly positive on the return of the last thirty minutes for both winner and loser stocks. Further, the volume of the first half hour and the overnight return both positively influences on the last half hour return of the day for loser stocks. This study can offer valuable insights for investment portfolio strategies, especially regarding intraday returns. The findings of this research prove to be a valuable resource for investors when devising investment strategies in the stock market. Additionally, it provides guidance for regulators in establishing rules for stock trading, particularly in transactions involving trading robots.

Keywords: volume, overnight return, intraday momentum, intraday return, USA Future Index, winner-loser portfolio.

Received: 20th February 2024
Accepted: 26th June 2024
https://doi.org/10.33736/ijbs.7630.2024

♣ Corresponding author: Universitas Andalas. Limau Manis, Pauh, Padang City, West Sumatra 25175, Indonesia. +62811665232. masyhurihamidi@eb.unand.ac.id

1. INTRODUCTION

In the operational activities of financial markets, technological advances have dramatically reduced trading costs in many financial markets because they reduce transaction costs and the cost of obtaining information (Dávila & Parlatore, 2021). This progress substantially increases high frequency trading (HFT) and is a striking aspect in financial markets due to easier transaction costs, lower information costs and more practical transaction processes (Chordia et al., 2011). Additionally, Malceniece et al. (2019) posited that apart from changes in fees, ease of transaction processing and information, the main change in financial markets over the past decade has been the development of trading algorithms (AT) and this is the reason for the emergence of automated trading strategies implemented on fast computers for short periods, known as high-frequency trading (HFT). HFT has a typical intraday and overnight trading patterns (Menkveld, 2014) which attracted academics scholars in examining trading behaviors caused by HFT (Li et. al, 2022). This condition prompts significant inquiries to understand the efficiency of the intraday market due to the increasing participation of traders in HFT.

Several studies have attempted to explain intraday returns. A study by Narayan and Sharma (2016) for instance, explores the prediction of intraday returns on the Chinese stock market using index futures from the US stock market. This research is based on the USA index futures which are a proxy for the macroeconomic conditions of the USA economy, because the movement of the future index is a positive relationship to economic sustainability (Sadalia et al., 2019). This study documents that index futures prices from the US spot market can predict intraday returns on the Chinese capital market. On the other hand, Gao et al. (2018) examined intraday momentum times series with the aim to observe the pattern of returns at the intraday level. This study found a positive return in the first thirty minutes of trading and the last thirty minutes of trading.

Lou et al. (2019) examined intraday returns and overnight returns and stated that intraday returns are based on the heterogeneity of investors consisting of intraday investors and overnight investors. It was found that a stock demonstrating intraday returns within a given month tends to exhibit similar intraday returns in the subsequent month, and vice versa. This result is different from other studies such as, Bogousslavsky (2021) who found that overnight return has a positive correlation with tomorrow's return except for the last half-hour return. Liu et al. (2015) added that overnight returns have a negative correlation with intraday returns the next day.

Huang et al. (2020) stated that overnight returns significantly predict intraday returns tomorrow where significant overnight returns predict returns in the first and last 30 minutes compared to morning returns. Additionally, Bogousslavsky (2021) posited that overnight return has a positive correlation with tomorrow’s return except with last half-hour return. But in contrast to the findings, Lou et al. (2019) argued that stocks that experience a high average overnight/intraday return in a month will also have a high average overnight/intraday return in the following month. Liu et al (2015) Overnight returns have a negative correlation with intraday returns the next day. This can be interpreted that today’s overnight return is used to predict tomorrow’s overnight return.

Furthermore, previous research has also shown a relationship between intraday returns and volume (Blau et al., 2018; Bogousslavsky, 2016; Chordia et al., 2011; Gao et al., 2018; Heston et al., 2010; Hussain, 2011), introduces U Shaped to trading volume, where volume is high in the morning and evening while in the period between the volume will be low. This can also be seen from the autocorrelation of morning and evening volumes. So that the volume has a strong predictive ability in predicting intraday returns on the US market. Furthermore, Han et al. (2022) examined the relationship between return and volume, they found that return is related to trading volume.

Stocks that exhibited positive performance in the past (winners) are likely to continue to perform well in the future and stocks that exhibited negative performance in the past (loser) are likely to continue to perform poor in the future (Jegadeesh & Titman, 1993). So that winner stocks and loser stocks display different patterns (Wouassom et al., 2022). The basic finding is “winners” (the top decile of performers) over the past three to twelve months continue to outperform “losers” (the bottom decile) over the next three to twelve months as well. This research has also been supported (Du et al., 2022; Maheshwari & Dhankar, 2017; Wouassom et al., 2022). This raises the opportunity to observe how the intraday return of winner and loser stocks.

Drawing from prior research, there is a limited amount of studies examining the impact of volume, overnight returns, and USA index futures on intraday returns for winner and loser stocks. This gap in research interest has prompted researchers to investigate further, aiming to address these aspects of intraday return.

The Indonesian capital market is chosen as the subject of this study due to its distinctive characteristics compared to previous research subjects in emerging markets (Adrianto & Hamidi, 2020; Chae and Kim, 2020; Hamidi & Adrianto, 2022). These distinctions encompass investor behavior, investor composition, information dissemination, regulations, and other factors (Aslam et al., 2020; Chae & Kim, 2020; İpek, 2021). Previous research related to intraday return and intraday momentum has predominantly been conducted in developed markets such as the United States and Europe. As for emerging market, most research is conducted on the Chinese stock market. However, the Chinese stock market is governed by a regulation that sets it apart from the Indonesian stock market. This regulation prohibits selling shares acquired on the same day but allows the purchase of shares sold on the same day (Qiao & Dam, 2020; Xiong et al., 2020). These differences in behavior, characteristics, and regulations are expected to provide distinct insights into the intraday returns of winner and loser stocks in the Indonesian capital market.

2. LITERATURE REVIEW

2.1. Intraday returns

Intraday return which is the basis of intraday momentum was first introduced by Wood et al. (1985). These findings form the basis of research by Gao et al. (2018) which proves that the first half-hour return can predict the last half-hour return through the momentum times series on ETFs in the United States. Momentum strategies from daily, weekly, and monthly periods to intraday emerged along with developments in information and communication technology which led to the emergence of high frequency trading (HFT). According to Brogaard et al. (2014), HFT improves investors' ability to obtain information and to analyze it and accelerates investor access in buying or selling actions in the market.

The concept of intraday momentum is also based on the intraday return (Sun et al., 2016; Renault, 2017; Zhang, Ma, & Zhu, 2019). Several previous studies examined intraday momentum, namely Gao et al. (2018) who examined intraday momentum in the United States

capital market and suggested that intraday return is determined by analyzing the correlation between the stock's return in the initial thirty minutes and its return in the final thirty minutes of trading. Linear regression is applied to assess the significance of intraday return. The findings of this research that the ability of intraday momentum to predict intraday returns was economically and statistically significant. Meanwhile, Zhang et al. (2019) examined intraday momentum in the Chinese stock market, and documented intraday momentum where the first half hour return can significantly predict the last half hour return. Li et al. (2022) expanded the research by examining intraday momentum at the international level using data from 16 developed countries capital markets and found that intraday momentum is economically and statistically significant. On the other hand, Devianto et al. (2018) and Hendershott et al. (2020) examined the relationship between systematic risk or stock beta on individual stock returns using the intraday period. It was found that return open to close (intraday) is negatively related. Furthermore, Bogousslavsky (2021) studies the intraday return anomaly. The study found significant evidence of positive morning returns in predicting intraday returns at the individual firm level. Following Gao et al. (2018), Zhang et al. (2019), Li et al. (2022), the first thirty-minute return is calculated by how much stock return is obtained in the first half hour when the market is open. The last thirty-minute return is calculated by how much stock return is obtained in the last half hour before the market closes. Based on the arguments above, the following hypothesis has been developed:
H1: Return of the first thirty minutes affects the return of the last half hour of winner and loser stocks.

2.2 Trading Volume

Volume shows the quality of a financial market. An increase in trading volume signifies an active and liquid market, reducing the cost of capital and fostering growth (Chordia et al., 2011). In addition to that, volume is one of the factors that has an influence on stock price movements as it displays the behavior of investors' herding to transact on a stock (Hsieh et al., 2020). Trading volume can be used as a tool to analyze the movement of a stock because trading volume actually describes the meeting between supply and demand for stock transactions (Heston et al., 2010) and volume has a pattern similar to stock returns (Gao et al., 2018). Following Heston et al. (2010), the first thirty minute volume is calculated by the volume of stock transactions in the first half hour the market is open.

Trading volume is a key element in predicting stock price movements (Heston et al., 2010). Hussain (2011) states that volume displays the flow of information received by investors, and that the volume changes in response to changes in information (Chordia et al., 2011). This trading volume is mostly represented by HFT (Boehmer et al., 2021). The development of HFT has caused many researchers to try to look more deeply at the development of trading volume theory. For instance, Heston et al. (2010) and Chordia et al. (2011) investigated patterns in intraday trading volume. They observed a U-shaped intraday pattern in trading volume, indicating higher volumes during the initial and final thirty minutes of market trading. Meanwhile, Hussain (2011) states that volume has a positive relationship with stock return volatility, which means that high volume will increase the volatility of stock returns. Furthermore, volume and return volatility have an intraday pattern. Bogousslavsky (2016) revealed that there is an intraday pattern of volume and stock returns, the volume pattern displayed is a U pattern. Based on the discussion above, the following hypohesis is posited:

H2: Volume in the first thirty minutes has an effect on returns in the last half hour of winner and loser stocks.

2.3 Overnight returns

Overnight return is based on the difference between the closing price and the opening price the following day (Hendershott et al., 2020). Branch and Ma (2012) examines how ETF prices move in the United States, which looks at intraday and overnight returns. Intraday and overnight relationships whether negative or positive can be seen through the autocorrelation between open to close, close to open and close to close. It was found that open to close has a negative autocorrelation, while close to open has a positive autocorrelation. The explanation for this condition is order imbalance or manipulation by market markers.

Overnight return is derived from the difference between the closing and opening prices on the following day. Typically, a stock closes within the bid and ask range at its closing (Bogousslavsky, 2021). Additionally, return close to open serves as compensation for overnight risk, where beta exhibits a positive correlation with return close to open (Hendershott et al., 2020). Following Lou et al. (2019), overnight return is calculated by the last half-hour return on the previous trading day. Hendershott et al. (2020) examined the relationship between systematic risk (or stock beta) on individual stock returns using intraday and overnight periods. This study found that return open to close (intraday) has a negative relationship with beta for intraday with an increase of 1 point the value of beta increases return overnight by 14 bps. Meanwhile, return close to open (overnight) is positively related to the value of an increase of 1 beta point which will reduce intraday return 15 bps. It displays the overnight return as a compensation for exposure to risk.

Bogousslavsky (2021) studies anomaly returns during day and night trading to explain what drives the predictability of cross-sectional returns. The effect of institutional constraints and overnight risk in explaining intraday return patterns, as well as using the factor of mispricing in testing this effect. The study found statistically significant evidence of a reversal between the 3:30–4:00 pm return and the following morning return. Based on the above discussion, the following hypothesis has been developed:
H3: Overnight return affects the return in the last half hour of winner and loser stocks.

2.4 The US Future Index

The US futures index serves as a proxy for the macroeconomic conditions of the US economy, as movements in the futures index reflect investors' assessment of the prospects of the stocks it represents. One of the primary factors influencing stock prices is the prospect of cash flows to be received by companies, which is highly dependent on macroeconomic conditions. Meanwhile, the Chinese stock market is affected by the US economic conditions in line with the strong economic relations between China and the USA where many Chinese companies whose income comes mostly from exports to the USA. Narayan and Sharma (2016) document that index futures prices from the US spot market can predict intraday returns on the Chinese capital market.

Robbani and Bhuyan (2016) examined the relationship between Dow Jones Industrial Average (DJIA) index future volatility and stock volatility. This study was undertaken to reconcile conflicting theories concerning the correlation between DJIA index futures volatility and the volatility of underlying stock returns. The findings indicate that DJIA index futures contribute to increased volatility in underlying stock returns. Furthermore, several studies have investigated the

relationship between the stock prices of a country in connection with the USA stock index, proxied by the DJIA index futures. Daily return of the United States Index futures is calculated by daily return of the United States index futures (Karaca et al., 2020; Kia et al., 2018; Malagrino et al., 2018). Based on the discussion above, the following hypothesis has been developed:
H4: The USA Futures Index in the first thirty minutes affects the return in the last half hour of winner and loser stocks.

3. METHODOLOGY

This study aims to examine the impact of volume, overnight returns, and US index futures on the intraday returns of both winning and losing stocks in the Indonesian capital market from July 2021 to June 2022. The first criteria for the sampling technique in this study are from companies whose shares are traded on the Indonesian Stock Exchange (IDX) from June 2021 to July 2022. Shares are selected from various sectors in the Indonesian capital market, such as the agricultural, mining, basic and chemical industries, various industries, consumer goods industries, property, infrastructure, finance and trade. Whilst the second criteria are where the company shares are actively traded during a trading day for at least thirty minutes. The secondary date utilised in this study are stock prices recorded every 30 minutes, trading volumes, and United States Futures index sourced. Subsequently, this dataset was analysed using the R studio and STATA statistical software version 13. A total of 3,876 observations were obtained and analysed.

The dependent variable in this analysis is the return during the last half hour, while the independent variable include returns for each half hour excluding the last one, as well as volume for each half hour, overnight return, and Dow Jones return. Stock return is calculated using the following formula:

$$R_{j,t} = \frac{P_{j,t} - R_{j,t-1}}{R_{j,t-1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (1)$$

Where, $R_{j,t}$ is stock return; $P_{j,t}$ is the stock price at t time; and $R_{j,t-1}$ is the stock price at t-1 time. Subsequently, these stocks are categorized into winner and loser stocks based on their return levels. High return is assigned to the top 10% of stocks with the highest returns, while low return is attributed to the bottom 10% with the lowest returns. Stocks with high returns are classified as winner stocks, while those with low returns are grouped as loser stocks (Chae & Kim, 2020; Dong et al., 2022; Kim & Suh, 2021).

The analysis technique employed in this study utilizes panel data regression to look at the ability of the first half hour return, first half hour volume, overnight return, and the United States futures index in predicting the last half hour return. This model is different from those of Gao et. al. (2018), Li et. al., (2022) and Zhang et al., (2019) which uses multiple linear regression, whilst panel data regression is employed in this study. The analysis of the dataset is facilitated by R Studio for organizing data matrices and STATA version 13 for processing panel data, enabling the assessment of the extent of impact of independent variables on the dependent variable.
The following regression equation model used is:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (2)$$

Where, Y is return of the last half hour return of the day; α is a constant; β_n is the regression coefficient of each variable; X_1 is return of the first half hour of the day; X_2 is volume of the first half hour; X_3 is the overnight return; X_4 is the daily return of the United States index futures; ε and is an error.

4. RESULTS AND DISCUSSION

From **Table 1**, the average intraday return for winner stocks is positive, while the average intraday return for loser stocks is negative. To examine the relationship between the return of the last thirty minutes with the return of the first thirty minutes, the volume of the first thirty minutes, the overnight return and the United States index futures, a panel data regression analysis was carried out.

Table 1: Descriptive statistic

Variable	Obs.	Mean	*SD*	Min	Max	Obs.	Mean	*SD*	Min	Max
	Winner					Loser				
Y	3876	0.001	0.007	-0.048	0.077	3876	0.000	0.007	-0.049	0.074
X_1	3876	0.038	0.028	-0.070	0.253	3876	-0.027	0.016	-0.070	0.055
X_2	3876	16.141	1.709	9.847	21.418	3876	15.502	1.692	9.259	21.105
X_3	3876	-0.001	0.007	-0.063	0.061	3876	0.002	0.009	-0.049	0.077
X_4	3876	0.000	0.010	-0.035	0.025	3876	0.000	0.010	-0.035	0.025

4.1 *Winner*

The panel data regression method used for the winner stocks in this study is the PLS model, the PLS model was chosen after selecting the model. However, after the classical assumption test was carried out and there was heteroscedasticity in the model, the model did not meet the Best Linear Unbiased Estimator (BLUE) requirements resulting in an inefficient estimation process. The method used to solve the problem of the PLS model that is not BLUE is by using the Generalised Least Square (GLS) method because this model has overcome the problem of heteroscedasticity.

Table 2: Regression Analysis Test Results for using the GLS Method

Variable	Winner	Loser
X_1	(0.011)**	(0.007)***
	0.025	-0.027
X_2	(0.000)	(0.000)***
	-0.000	-0.000
X_3	(0.040)*	(0.013)***
	0.076	0.052
X_4	(0.029)	(0.012)*
	0.006	0.021
Cons.	(0.003)	(0.001)
	-0.000	0.003
Hausman test		0.000
LM test	1.000	
Breusch-Pagan/Cook-Weisberg test	0.000	
Wald test		0.000
Mean VIF	1.10	2.53
Number of Observation	3876	3876
R-squared	0.003	0.010
F-Stat.	0.032	0.000

Notes: *,**,***Significant 10, 5 and 1 per cent levels, respectively. Standard error in the parenthesis

Based on the results depicted in **Table 2**, it can be seen that for winner stocks, only variable X1 (first thirty-minute return) has a significant effect on Y (last thirty-minute return) with a significance level of 0.025, less than 0.05 (5%). Variable X3 overnight return significantly affects Y with a significance level of 10 percent with a significance value of 0.058, while other variables do not significantly affect Y. The R-square value of this equation model is 0.0027 or equal to 0.27 percent. This R-square value is much smaller than that obtained (Gao et al., 2018) which is 3.3 percent.

The research findings on winning stocks are in line with the discoveries of Gao et al. (2018), Zhang et al. (2019), and Li et al. (2022), which demonstrate that the first half-hour return can forecast the last half-hour return. However, these results are not consistent with the studies conducted by Heston et al. (2010), Chordia et al. (2011), and Bogousslavsky (2016), which document that the trading volume in the first thirty minutes influences the return in the last thirty minutes. Furthermore, this research is not aligned with the findings of Lou et al. (2019), and Bogousslavsky (2021), which illustrate the relationship between overnight trading and the return in the last thirty minutes. It also contradicts the research by Narayan and Sharma (2016), and Robbani and Bhuyan (2016), which document that the USA future index is able to predict the return in the last thirty minutes.

4.2 *Loser*

Based on **Table 2**, it can be seen that for loser stocks the variables X1 (first thirty minute-return), X2 (first thirty minute volume) and X3 (overnight return) have a significant effect on Y (last thirty minute return) with a significance level of 0.000 smaller of 0.05 (5%). Variable X4 (USA futures index) significantly affects Y with a significance level of 10 percent with a significance value of 0.074. The R-square value of this equation model is 0.0101 or equal to 1.01 percent. This R-square value is much smaller than that obtained (Gao et al., 2018) which is 3.3 percent.

The research results for loser stocks are in line with the findings of Gao et al. (2018), Zhang et al. (2019), and Li et al. (2022) which prove that returns in the first half hour can predict returns in the last half hour. This research is also consistent with Heston et al. (2010), Chordia et al. (2011), and Bogousslavsky (2016) who documents that trading volume in the first thirty minutes has an impact on returns in the last thirty minutes. In addition, this research is in line with the research results of Lou et al. (2019), and Bogousslavsky (2021) which shows that there is a relationship between overnight returns and the last thirty minutes. However, in contrast to Narayan and Sharma (2016), and Robbani and Bhuyan (2016) noted that the USA futures index was able to predict returns in the last thirty minutes.

The differential impact of independent variables on the dependent variable between the winner and loser stock groups indicates variations in investor behavior towards these stock categories. Winner stocks exhibit investor underreaction and price continuation behavior, leading to an increase in stock prices in the afternoon. In contrast, loser stocks show investor overreaction and price reversal behavior, causing prices to reverse direction in the afternoon. However, for the loser stock group, overreaction behavior and price reversal are influenced by overnight return and volume in the first thirty minutes of stock trading.

The findings of this study reveal that investor underreaction and overreaction behavior, as well as stock price continuation and price reversal patterns, persist in the intraday trading dynamics of both winner and loser stock groups.

4.3 *Robustness check*

To strengthen the interpretation of existing research results, this study follows those of Gao et al. (2018), Zhang et al. (2019), Gao and Liu (2020), Azevedo (2022), and Wen et al. (2022) who evaluated the predictive power using out-of-sample. The day effect is to see how the ability of exogenous variables to explain endogenous variables when sorted by different days is in line with the research of (Chu & Song, 2023).

Several alternatives were developed to verify the model's construction. First, we analyzed the models using recursive for each stock of winners and losers, as well as their combination (hybrid model). Second, an analysis was conducted using event study for each active market day. Third, comparing the results of the three analyses conducted for each winner and loser stock **Table 3** and the hybrid model **Table 4**. The analysis results of the hybrid model shown in table 5 indicate that the comparison of each variable with significance below 10 percent and above 10 percent mostly yields identical outcomes. Finally, **Table 4** also shows that the analysis of the baseline is generally identical and stable for each winner and loser stock.

5. CONCLUSION

Result from this study demonstrates that alterations in stock returns during the first thirty minutes are subsequently mirrored by changes in stock returns during the last thirty minutes for both winner and loser stock groups, hence, Hypothesis 1 is accepted. For the direction of change in the winner stock group, the first thirty minute return has a positive effect with the last thirty minute return, and in line with most of prior studies (Aitken et al., 2015; Bogousslavsky, 2021; Gao et al., 2018; Li et al., 2022; Lou et al., 2019). Conversely, the loser stock group has a negative direction of change, and in line with those of Andersen et al. (2022), Kang et al. (2022), Hendershott et al. (2020), and Chu and Song (2023). Several factors contribute to this adverse impact, including market-maker behavior, specialist behavior as documented in literature, bid-ask bounces, and alternative explanation (Andersen et al., 2022; Seok et al., 2021).

When evaluating Hypothesis 2, acceptance is only observed within the loser stock category. Volume is a proxy for the arrival of information which affects intraday returns and has an intraday pattern. These results show that for intraday anomaly loser stocks are also displayed by volume, where volume displays a negative relationship and contrary to Heston et al. (2010), Chordia et al. (2011), Hussain (2011), Bogousslavsky (2016), Gao et al. (2018), and Hsieh et al. (2020). Hypothesis 3 focuses on assessing the impact of overnight returns on returns during the last thirty minutes. The findings indicate that only loser stocks exhibit a significant and positive effect on intraday returns during the last thirty minutes. This aligns with the research findings of Branch and Ma (2012), Bogousslavsky (2016), and Hendershott et al. (2020).

Meanwhile for Hypothesis 4, which posits that the USA Index futures act as a proxy for the macroeconomic conditions of the US economy influencing intraday returns, is not supported. This contradicts with the findings of Narayan and Sharma (2016). Consequently, investors may consider incorporating volume and overnight returns into their intraday trading strategies to achieve intraday returns.

This study has tested and proved that there are intraday returns for the winner and loser stock groups, changes in stock returns in the first thirty minutes will be followed by changes in stock returns in the thirty minutes. Furthermore, for the influence of volume variables and overnight returns, they only affect intraday returns for the loser stock group. Meanwhile, the USA index futures variable does not significantly affect intraday returns on either winner or loser stocks.

This research can serve as a valuable reference for investors in formulating investment strategies in the capital market. Additionally, for regulatory authorities, the findings of this study can be a source for crafting rules in stock trading, particularly in transactions involving trading robots or automation, aiming to enhance market efficiency with the implementation of trading technologies. The research outcomes, focusing on intraday return, may provide a foundation for further studies such as the development of intraday momentum portfolio strategies and intraday asset pricing.

Table 3: Robustness check (winner and loser)

	(1)		**(2)**		**(3)**									
	Baseline		**Recursive**		**Event study**									
					Monday		Tuesday		Wednesday		Thursday		Friday	
	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
	GLS	GLS	GLS	GLS	GLS	PLS	GLS	PLS	GLS	GLS	PLS	PLS	GLS	GLS
X_1	(0.011)**	(0.007)***			(0.009)	(0.014)	(0.059)	(0.018)**	(0.010)***	(0.016)*	(0.010)**	(0.010)**	(0.011)	(0.029)
	0.025	-0.027			0.008	-0.016	0.047	-0.037	0.031	-0.031	0.024	0.024	0.010	-0.025
X_2	(0.000)	(0.000)***		(0.000)**	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)***	(0.000)	(0.000)	(0.000)	(0.000)***
	-0.000	-0.000		-0.000	-0.000	-0.000	0.001	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
X_3	(0.040)*	(0.013)***		(0.019)***	(0.035)***	(0.023)**	(0.190)	(0.038)	(0.035)*	(0.029)*	(0.037)	(0.037)	(0.037)*	(0.051)
	0.076	0.052		0.052	0.105	0.047	0.119	0.054	0.068	0.055	0.014	0.015	0.073	0.019
X_4	(0.029)	(0.012)*			(0.023)	(0.022)*	(0.147)	(0.028)**	(0.027)	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)
	0.006	0.021			-0.008	-0.037	-0.094	-0.057	0.009	-0.034	-0.014	-0.014	0.022	0.020
Cons.	(0.003)	(0.001)		(0.002)	(0.002)	(0.002)	(-0.014)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
	-0.000	0.003		0.003	0.004	0.001	-0.013	0.002	0.000	0.007	0.003	0.003	0.002	0.005
Hausman test		0.000											0.111	0.907
LM test	1.000			0.490	1.000	0.425	1.000	1.000	0.234	0.116	1.000	1.000		
Wald test		0.000	0.000											0.000
Breusch-Pagan/Cook-Weisberg test	0.000			0.000	0.028	0.169	0.000	0.263	0.000	0.000	0.642	0.642		
Mean VIF	1.10	2.53	1.11	1.01	1.09	1.09	1.11	1.05	1.13	1.06	1.11	1.11	1.94	2.78
Num. of Obs.	3876	3876	1938	1428	799	799	765	765	748	748	782	782	782	782
R-squared	0.003	0.010	0.007	0.009	0.015	0.013	0.004	0.013	0.022	0.024	0.008	0.008	0.010	0.010
F-Stat.	0.032	0.000		0.002	0.019	0.038	0.029	0.039	0.002	0.001	0.165	0.165	0.1975	0.309

Notes: *,**,***Significant 10, 5 and 1 per cent levels, respectively. Standard error in the parenthesis. Table 3 shows the results of a comparison between baseline, recursive, and event study analysis on winners and losers stock. Each method utilizes its respective estimation, and regression models, tests for multicollinearity, and heteroskedasticity have been conducted. The results of the event study are based on the days when the market was open.

Table 4: Robustness check (hybrid model)

	(1)	(2)	(3)				
	Baseline	**Recursive**	**Event study**				
			Monday	Tuesday	Wednesday	Thursday	Friday
X_1	(0.000)***	(0.000)***	(0.007)	(0.008)	(0.004)***	(0.004)***	(0.009)
	0.000	0.000	0.010	0.011	0.020	0.017	-0.011
X_2	(0.000)***		(0.000)*	(0.000)	(0.000)	(0.000)*	(0.000)***
	0.000		-0.000	0.000	-0.000	-0.000	-0.000
X_3	(0.005)***	(0.006)***	(0.010)***	(0.024)***	(0.005)**	(0.011)***	(0.012)***
	0.026	0.022	0.066	0.083	0.012	0.062	0.077
X_4	(0.004)		(0.006)	(0.015)	(0.001)	(0.007)*	(0.007)
	0.002		-0.016	0.015	-0.006	0.016	-0.007
Cons.	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	-0.002	-0.000	0.000	-0.001	0.000	0.001	0.008
Hausman test	0.008	0.001	0.026				0.001
Lagrangian multiplier test				1.000	0.188	1.000	
Wald test	0.000	0.000	0.000				0.000
Breusch-Pagan/Cook-Weisberg test				0.000	0.000	0.0004	
Mean VIF	3.49	1.02	1.02	1.03	1.01	1.01	1.02
Number of Observation	40128	14784	8272	7920	7744	8096	8096
R-squared	0.002	0.006	0.003	0.002	0.005	0.007	0.002
F-Stat.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: *,**,***Significant 10, 5 and 1 per cent levels, respectively. Standard error in the parenthesis. Table 4 shows the results of a comparison between baseline, recursive, and event study analysis on all stocks (comprising winner and loser stocks). Each of these methods has undergone appropriate regression model testing, multicollinearity tests, and heteroskedasticity tests, with all estimations utilizing the Generalised Least Square (GLS) approach. The results of the event study are based on the days when the market was open.

Table 5: Variables Definitions

Variable	Definition	Reference
The last thirty-minutes return (Y)	How much stock return is obtained in the last half hour before the market closes	Gao et al. (2018); Zhang et al. (2019); Li et al. (2022)
The first thirty minutes return (X_1)	How much stock return is obtained in the first half hour when the market is open	Gao et al. (2018); Zhang et al. (2019); Li et al. (2022)
The first thirty minutes volume (X_2)	The volume of stock transactions in the first half hour the market is open	Heston et al., 2010
Overnight return (X_3)	The last half-hour return on the previous trading day	Lou et al., 2019
Daily return of the United States Index futures (X_4)	The daily return of the United States index futures	Karaca et al. (2020); Kia et al. (2018); Malagrino et al. (2018)

REFERENCES

Adrianto, F., & Hamidi, M. (2020). Analysis of Retail Investment Behaviour in Indonesian Stock Market. *Academy of Accounting and Financial Studies Journal*, *24*(2), 2635–2649.

Aitken, M., Cumming, D., & Zhan, F. (2015). High frequency trading and end-of-day price dislocation. *Journal of Banking and Finance*, *59*(June), 330–349. https://doi.org/10.1016/j.jbankfin.2015.06.011

Andersen, T. G., Riva, R., Thyrsgaard, M., & Todorov, V. (2022). Intraday cross-sectional distributions of systematic risk. *Journal of Econometrics*, 235(2), 1394–1418. https://doi.org/10.1016/j.jeconom.2022.11.001

Aslam, F., Memon, B. A., & Mughal, K. S. (2020). Risk-adjusted and Bonferroni-adjusted seasonality in emerging Asian stock markets. *Economic Journal of Emerging Markets*, *12*(1), 80–92. https://doi.org/10.20885/ejem.vol12.iss1.art7

Azevedo, V. (2022). Analysts' Underreaction and Momentum Strategies. *Journal of Economic Dynamics and Control*, 49(2), 1–49. https://doi.org/10.2139/ssrn.4095711

Blau, B. M., Griffith, T. G., & Whitby, R. J. (2018). The maximum bid-ask spread. *Journal of Financial Markets*, *41*, 1–16. https://doi.org/10.1016/j.finmar.2018.09.003

Boehmer, E., Fong, K., & Wu, J. (2021). Algorithmic Trading and Market Quality: International evidence. *Journal of Financial and Quantitative Analysis*, *56*(8), 2659–2688.

Bogousslavsky, V. (2016). Infrequent Rebalancing, Return Autocorrelation, and Seasonality. *Journal of Finance*, *71*(6), 2967–3006. https://doi.org/10.1111/jofi.12436

Bogousslavsky, V. (2021). The cross-section of intraday and overnight returns. *Journal of Financial Economics*, *141*(1), 172–194. https://doi.org/10.1016/j.jfineco.2020.07.020

Branch, B. S., & Ma, A. (2012). Overnight Return, the Invisible Hand Behind the Intraday Return? A Retrospective. *Journal of Applied Finance*, *22*(2), 1–11. https://doi.org/10.2139/ssrn.3259614

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *Review of Financial Studies*, *27*(8), 2267–2306. https://doi.org/10.1093/rfs/hhu032

Chae, J., & Kim, R. (2020). Contrarian profits of the firm-specific component on stock returns. *Pacific Basin Finance Journal*, *61*, 101176. https://doi.org/10.1016/j.pacfin.2019.101176

Chordia, T., Roll, R., & Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. *Journal of Financial Economics*, *101*(2), 243–263. https://doi.org/10.1016/j.jfineco.2011.03.008

Chu, X., & Song, S. (2023). Cross-sectional reversal of intraday returns and investor heterogeneity in an emerging market. *Borsa Istanbul Review, 23*(3), 614–627. https://doi.org/10.1016/j.bir.2023.01.002

Dávila, E., & Parlatore, C. (2021). Trading Costs and Informational Efficiency. *Journal of Finance*, *76*(3), 1471–1539. https://doi.org/10.1111/jofi.13008

Devianto, D., Maiyastri, Randy, Hamidi, M., Maryati, S., & Wirahadi Ahmad, A. (2018). Efficiency analysis of optimal portfolio selection for stocks in LQ45 index. *Proceedings of ICAITI 2018 - 1st International Conference on Applied Information Technology and Innovation: Toward A New Paradigm for the Design of Assistive Technology in Smart Home Care*, 78–83. https://doi.org/10.1109/ICAITI.2018.8686713

Dong, L., Dai, Y., Haque, T., Kot, H. W., & Yamada, T. (2022). Coskewness and reversal of momentum returns: The US and international evidence. *Journal of Empirical Finance*, *69*(2), 241–264. https://doi.org/10.1016/j.jempfin.2022.10.004

Du, Q., Liang, D., Chen, Z., & Tu, J. (2022). Concept links and return momentum. *Journal of Banking and Finance*, *134*, 106329. https://doi.org/10.1016/j.jbankfin.2021.106329

Gao, B., & Liu, X. (2020). Intraday sentiment and market returns. *International Review of Economics and Finance*, *69*(3), 48–62. https://doi.org/10.1016/j.iref.2020.03.010

Gao, L., Han, Y., Zhengzi Li, S., & Zhou, G. (2018). Market intraday momentum. *Journal of Financial Economics*, *129*(2), 394–414. https://doi.org/10.1016/j.jfineco.2018.05.009

Hamidi, M., & Adrianto, F. (2022). Government officers: Do they have a better retirement planning? *Kasetsart Journal of Social Sciences*, *43*, 645–652.

Han, Y., Huang, D., Huang, D., & Zhou, G. (2022). Expected return, volume, and mispricing. *Journal of Financial Economics*, *143*(3), 1295–1315. https://doi.org/10.1016/j.jfineco.2021.05.014

Hendershott, T., Livdan, D., & Rösch, D. (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics*, *138*(3), 635–662. https://doi.org/10.1016/j.jfineco.2020.06.006

Heston, S. L., Korajczyk, R. A., & Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *Journal of Finance*, *65*(4), 1369–1407. https://doi.org/10.1111/j.1540-6261.2010.01573.x

Hsieh, S. F., Chan, C. Y., & Wang, M. C. (2020). Retail investor attention and herding behavior. *Journal of Empirical Finance*, *59*, 109–132. https://doi.org/10.1016/j.jempfin.2020.09.005

Huang, D., Li, J., Wang, L., & Zhou, G. (2020). Time series momentum: Is it there? *Journal of Financial Economics*, *135*(3), 774–794. https://doi.org/10.1016/j.jfineco.2019.08.004

Hussain, S. M. (2011). The Intraday Behaviour of Bid-Ask Spreads, Trading Volume and Return Volatility: Evidence from DAX30. *International Journal of Economics and Finance*, *3*(1), 23–34. https://doi.org/10.5539/ijef.v3n1p23

İpek, İ. (2021). The relevance of international marketing strategy to emerging-market exporting firms: from a systematic review towards a conceptual framework. *International Marketing Review*, *38*(2), 205-248. https://doi.org/10.1108/IMR-02-2020-0017

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65–91. http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1993.tb04702.x/abstract

Kang, J., Lin, S., & Xiong, X. (2022). What drives intraday reversal? Illiquidity or liquidity oversupply?. *Journal of Economic Dynamics and Control*, *136*, 1–73.

https://doi.org/10.1016/j.jedc.2022.104313

Karaca, Y., Zhang, Y. D., & Muhammad, K. (2020). Characterizing complexity and self-similarity based on Fractal and Entropy analyses for Stock Market Forecast Modelling. *Expert Systems with Applications*, *144,* 113098. https://doi.org/10.1016/j.eswa.2019.113098

Kia, A. N., Haratizadeh, S., & Shouraki, S. B. (2018). A hybrid supervised semi-supervised graph-based model to predict one-day ahead movement of global stock markets and commodity prices. *Expert Systems with Applications*, *105*, 159–173. https://doi.org/10.1016/j.eswa.2018.03.037

Kim, B., & Suh, S. (2021). Overnight stock returns, intraday returns, and firm-specific investor sentiment. *North American Journal of Economics and Finance*, *55*(3), 101287. https://doi.org/10.1016/j.najef.2020.101287

Li, Z., Sakkas, A., & Urquhart, A. (2022). Intraday time series momentum: Global evidence and links to market characteristics. *Journal of Financial Markets*, *57*, 100619. https://doi.org/10.1016/j.finmar.2021.100619

Liu, Q., Guo, H., & Wei, X. (2015). Negative overnight returns: China's security markets. *Information Technology and Quantitative Management (ITQM), 55*(1), 980–989. https://doi.org/10.1016/j.procs.2015.07.105

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, *134*(1), 192–213. https://doi.org/10.1016/j.jfineco.2019.03.011

Maheshwari, S., & Dhankar, R. S. (2017). Momentum Anomaly: Evidence from the Indian Stock Market. *Journal of Advances in Management Research*, *14*(1), 3–22. https://doi.org/10.1108/JAMR-11-2015-0081

Malagrino, L. S., Roman, N. T., & Monteiro, A. M. (2018). Forecasting stock market index daily direction: A Bayesian Network approach. *Expert Systems with Applications*, *105*, 11–22. https://doi.org/10.1016/j.eswa.2018.03.039

Malceniece, L., Malcenieks, K., & Putniņš, T. J. (2019). High frequency trading and comovement in financial markets. *Journal of Financial Economics*, *134*(2), 381–399. https://doi.org/10.1016/j.jfineco.2018.02.015

Menkveld, A. J. (2014). High-frequency traders and market structure. *Financial Review*, *49*(2), 333–344. https://doi.org/10.1111/fire.12038

Narayan, P. K., & Sharma, S. S. (2016). Intraday return predictability, portfolio maximisation, and hedging. *Emerging Markets Review*, *28,* 105–116. https://doi.org/10.1016/j.ememar.2016.08.017

Qiao, K., & Dam, L. (2020). The overnight return puzzle and the "T+1" trading rule in Chinese stock markets. *Journal of Financial Markets*, *50*, 100534. https://doi.org/10.1016/j.finmar.2020.100534

Renault, T. (2017). Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking and Finance, 84,* 25–40. https://doi.org/10.1016/j.jbankfin.2017.07.002

Robbani, M. G., & Bhuyan, R. (2016). Introduction of Futures and Options on a Stock Index and their Impact on the Trading Volume and Volatility: Empirical Evidence from the DJIA Components. In S. Satchell (Eds.), *Derivatives and Hedge Funds* (pp. 187–201). Palgrave Macmillan. https://doi.org/10.1057/9781137554178_9

Sadalia I., Irawati N., Hamidi M., Giriati G., Yuliana S. (2019). How the financial opennes accelerates the economic growth of leading Asean economies. *Journal of Security and Sustainability Issues*, *9*(2), 473-487.

Seok, S. I., Cho, H., & Ryu, D. (2021). Stock Market's responses to intraday investor sentiment.

North American Journal of Economics and Finance, *58*, 101516. https://doi.org/10.1016/j.najef.2021.101516

Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking and Finance*, *73*, 147–164. https://doi.org/10.1016/j.jbankfin.2016.09.010

Wen, Z., Bouri, E., Xu, Y., & Zhao, Y. (2022). Intraday return predictability in the cryptocurrency markets: Momentum, reversal, or both. *North American Journal of Economics and Finance*, *62*, 101733. https://doi.org/10.1016/j.najef.2022.101733

Wood, R. A., McInish, T. H., & ORD, J. K. (1985). An investigation of transactions data for NYSE Stocks. *The Journal of Finance*, *40*(3), 723–739. https://doi.org/10.1111/j.1540-6261.1985.tb04996.x

Wouassom, A., Muradoğlu, Y. G., & Tsitsianis, N. (2022). Global momentum: The optimal trading approach. *Journal of Behavioral and Experimental Finance*, *36*, 100756. https://doi.org/10.1016/j.jbef.2022.100756

Xiong, X., Meng, Y., Li, X., & Shen, D. (2020). Can overnight return really serve as a proxy for firm-specific investor sentiment? Cross-country evidence. *Journal of International Financial Markets, Institutions & Money*, *64*(92), 101173. https://doi.org/10.1016/j.intfin.2019.101173

Zhang, Y., Ma, F., & Zhu, B. (2019). Intraday momentum and stock return predictability: Evidence from China. *Economic Modelling*, *76*, 319–329. https://doi.org/10.1016/j.econmod.2018.08.009