

THE IMPACT OF INTRADAY MOMENTUM ON STOCK RETURNS: EVIDENCE FROM S&P500 AND CSI300

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Abstract: This paper analyzes the statistical impact of COVID-19 on the S&P500 and the CSI300 intraday momentum. This study employs an empirical method, that is, the intraday momentum method used in this research. Also, the predictability of timing conditional strategies is also used here to predict the intraday momentum of stock returns. In addition, this study aims to estimate and forecast the coefficients in the stock market pandemic crisis through a robust standard error approach. The empirical findings indicate that the intraday market behavior an unusual balanced; the volatility and trading volume imbalance and the return trends are losing overwhelmingly. The consequence is that the first half-hour return will forecast the last half-hour return of the S&P500, but during the pandemic shock, the last half-hour of both stock markets will not have a significant impact on intraday momentum. Additionally, market timing strategy analysis is a significant factor in the stock market because it shows the perfect trading time, decides investment opportunities and which stocks will perform well on this day. Besides, we also found that when the volatility and volume of the S&P500 are both at a high level, the first half-hour has been a positive impact, while at the low level, the CSI300 has a negative impact on the last half-hour. In addition, this shows that the optimistic effect and positive outlook of the stockholders for the S&P500 is in the first half-hours after weekend on Monday morning because market open during the weekend holiday, and the mentality of every stockholder's indicate the positive impression of the stock market.

Keywords: COVID-19, intraday momentum, stock market, predictability, Volatility and Volume.

JEL Classification: C13, C33, C41, E44, G14.

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Introduction

According to data from the World Health Organization (WHO, 2020), the Coronavirus (COVID-19) outbreak in late December has spread to 216 countries, territories or regions,

causing more than 21.5 (214,435,732) million confirmed casualties and 4,471,650 deaths worldwide on August 26, 2021. Due to the large and continuous spread of the novel coronavirus worldwide, on March 11, 2020,

the WHO officially declared it a pandemic (Mahmud et al., 2021). In most economies, the COVID-19 pandemic has caused uncertainty and a temporary closure with positive cases coronavirus. Therefore, the purpose of this article is to assess the significant impact of the COVID-19 pandemic on intraday stock returns. Many investors close their holdings, including the stock market's assets, thereby influencing the stock market. According to Jegadeesh and Titman (1993), the stock purchase method is appropriate when stock sales have performed poorly during the holding period of past 3-months to the 12-months. Besides, these forms of momentum gain are inappropriate to justify risk-based momentum. In exchange for 1 to 12 months (Moskowitz et al., 2012), the persistence in partially changed in a longer horizon. A timely competitive strategy across all asset classes yield a large abnormal return and is rarely influenced by traditional asset pricing factors. In this regard, Asness et al. (2013) reliably defines value and momentum return prices of eight different conditions and asset groups. The robust standard factor structure between returns, valuation and momentum have a greater correlation with asset classes. Zhang et al. (2018) shows that in conjunction with iterative prediction, the sample values and higher performance ratios frequently produce results that are significantly higher than related regular combination predictions. To the best of our knowledge, momentum techniques can be return patterns every hour, day, week, or month. This dynamic intraday trend is shown by Gao et al. (2018), who announced that the first half hour's market return is expected to be the last half hour measured from the previous day's market close.

In our study, we investigate the intraday momentum of the S&P500 and CSI300 index data for three primary reasons. First, in politics, the USA is globally positioned, while China stands at the second economic growth position. Secondly, we know that investors and brokerage companies are interested in investing in these two countries' financial sectors. Naseer et al. (2021) revealed that the stock market is positively related with financial performance. The third reason is the impact of COVID-19 pandemic on stock markets. According to the analysis of Mazur et al. (2021), COVID-19's crash in the US market price in March 2020 displays asymmetric

volatility, and stock returns are negatively correlated. Phan and Narayan (2020) shows that the stock price overreacted to different stages of COVID-19's evolution and expected news, and the market. As more information becomes available and people understand the consequence more widely, the market will correct itself. Ramelli and Wagner (2020), and Wagner (2020) demonstrate that COVID-19 represents a fearsome and novel risk. When volatility and economic expectations basis for individual companies' stock prices fluctuations, it will arouse investors' fanaticism. Just and Echaust (2020) suggest that there is a close dependence between stock returns and implied volatility and implied correlation, however, it has nothing to do with liquidity. Besides, Topcu and Gulal (2020) found that the negative impact on emerging stock markets has gradually declined and began to gradually taper off by mid-April. The stock market returns decline as the number of confirmed cases compared increases to the growth in the number of deaths (Ashraf, 2020). Baker et al. (2020) pointed out that in a service-oriented economy, the proposed government barriers to trade and voluntary social distancing are strong. This is the critical reason why the US stock market has responded COVID-19 so strongly. On the other hand, the COVID-19 pandemic has had a significant influence on the real economy, causing to a global lockdown that lasted several months and affected both stock markets. Therefore, it is important to investigate how this global shock affects stock market trading behavior.

Generally, according to the micro-foundation, the momentum volatility can take two forms; as Bogouslavsky (2016) stated that unusual portfolios can boost theoretical investors' intraday momentum. Likewise, Murphy and Thirumalai (2017) proved that companies are explicitly re-equilibrated by frequent ordering with data from real brokerage accounts utilizing such periodic revaluation. The slow capital flow and several structural factors of some institutional developers may compensate for the investments in the first half-hour. On the other hand, the same organizations rebalanced within the last half hour by even or others trade in the same way as the first one yields the executed dynamic intraday model.

The observed intraday momentum pattern can be generated by trading in the same direction as the first half-hour. The second

hypothesis is based on late buyers who pass information early in the last half hour. The last half-hour exchange allows people who get information late or cannot deal with details to escape nocturnal hazards and use high liquidity. Besides, late customers in the last half-hour follow the same way as the first half-hour of the day. As a result, late-informed investors' trading in the last half hour would follow the same trend as the first half-hour, creating intraday momentum.

The intraday momentum is more substantial than another momentum. It also endures after reasonable transaction costs are considered; in addition to the S&P500 index, it is also strong and significant for eleven other most actively traded ETFs in the US Alternative stock indices, such as the Dow Jones Industrial Average and the Nasdaq Composite Index. Financial, real estate, bonds, and select international equity indices are also covered.

In COVID-19 shocks, our paper is related to the literature on intraday momentum of trading activity. Many researches on this topic have focused on trading activity and volatility (see, e.g., Chordia et al., 2011; Corwin & Schultz, 2012; Heston et al., 2010; Murphy & Thirumalai, 2017) and our research is more closely related. They found significant evidence that the returns on particular equity are consistent within the half-hour intervals across the trading day. In the theoretical model on infrequent rebalancing, Bogousslavsky (2016) discussed this particular association in detail. In contrast to this research, we examine the intraday momentum of the market, which is based on the predictability of the market's first half-hour returns based to the market's final half-hour returns on the same day. Based on the concept and goal objectives of our manuscript, we formulated hypothesis to investigate the impact of intraday momentum on S&P500 and CSI300 stock returns. Whatever, during the COVID-19 pandemic, volatility is significantly higher. Based on this concept, this study also identifies the time when utilizing overreaction behavior, reverse strategy has comparatively lower return. Timing conditional predictivity is found to have significant effects on these results. The conclusions of this study have important implications for investors, portfolio managers, and legislators in investing strategies and stock market supervision, both of which may have a significant influence on the market. According to our study on the

COVID-19 situation, investors should use buy and hold strategies, a timing strategy, a day-by-day approach, and a good portfolio planning. Our findings also help to better understand other aspects of intraday momentum and protect investors from COVID-19 shocks.

Thus, the above discussion mentioned the serious impact of COVID-19 on economy, especially on the stock market. In addition, China and the USA are the main victims of the COVID-19 that drastically affected their economies and stock markets. Moreover, when the US stock markets are affected simultaneously, other stock markets will also be affected at the same time because all markets are intercorrelated. Therefore, in order to survive, solving the existing damages of COVID-19 has become an essential requirement of the economies. In this regard, the present study attempts to examine the intraday momentum of the USA and China stock markets during the COVID-19 situation.

Moreover, most of the past research supports the presence of the stock market reaction trend and the profitability of the contrarian strategy. The profitability of the contrarian strategy, on the other hand, varies depending on the time frame (short-term, medium-term, or long-term) and the firm's size. By using intraday data (1 minute), depending on a dynamic statistical method to estimate stock return forecast, examining stock index, and considering a potential effect of the COVID-19 epidemic on overreacting behavior, our work has made a contribution to the present literature. However, to the best of our knowledge, there is no study has used intraday data and a dynamic technique to evaluate the intraday momentum stock price during pandemic. In our opinion, it is important to assess the stock market since its fundamental value significantly differs from that of daily stocks. In this case, volatility and trading volume are the most crucial determinants of its intrinsic value; however, these factors are primarily tied to company's dynamics in the stock market.

This paper has organized as follows; Section 2 details the literature review; Section 3 describes the data and intraday momentum methodology; section 4 empirical results analysis, robustness checks, and discussions on intraday momentum in two stock markets during COVID-19. Finally, section 5 discussion and section 6 states the conclusions of the study.

1. Literature Review

Studies based on the movements of stock values in the leading economies shows that intraday momentum indexes help investors make better trading decisions in the stock markets (Chu et al., 2019). These studies illustrate the significance of intraday momentum index among investors as it is a technical indicator that uses candlestick analysis and relative strength analysis. These studies propose that the intraday momentum index is used to analyze the correlation between the opening and closing prices of a particular security, like share or bond, in a day, rather than the opening and closing prices of security across days or weeks. Technical analysts use this indicator to predict whether a security is overbought or oversold (Li et al., 2020). Due to globalization, environmental changes and urban expansion, a prolonged disease broke out, which results in worldwide threats that need to be jointly replied to by the economies across the world (Baker et al., 2020). According to the proposal from International Monetary Fund (IMF), the contagious disease COVID-19 triggered a very different economic crisis from the past. This difference is that it is more multifaceted, unpredictable, and at the same time it has a substantial impact simultaneously across the world. It has disrupted the social and economic structure since individual consumers, businesses, and investments have gone downward (Mazur et al., 2021). Hence, the stock markets were adversely affected during the COVID-19 pandemic, especially at the initial stage, as it harmed health and compromised its security.

Compared to the other price index, the intraday momentum index has become famous for checking the movement in securities prices in stock markets such as the USA and China stock markets. Researchers are interested in investigating the return predictability through an appropriate technical price indicator (such as intraday momentum index), which would help make investment decisions in typical stock markets and stock markets facing the impact of contagious pandemics like COVID-19 (Wagner, 2020). Since both USA and China stock markets are considered to be the most important stock markets in the world, Li et al. (2020) explored the association between economic variables and stock returns in the USA and China. They revealed that order imbalance and S&P500

have also successfully forecasted the stock returns in the Chinese economy under particular trading frequency. These studies show that the trading hours of US stock markets are from 9:30 to 16:00 Eastern Time.

In contrast, in the Chinese stock markets, the trading hours are from 9:30 to 11:30 and 13:00 to 15:00 Beijing Time. This difference in trading hours may lead to a difference in intraday momentum patterns of the two countries' stock markets. Thus, the half-hour returns of Chinese stock markets is only 8 on each trading day, while they are more in number in the case of USA stock markets (Xu et al., 2020). In addition, the closing time of the stock market trading day will also affect the intraday momentum index. During the COVID-19 pandemic, stock market trading mechanisms in both countries and other parts of the world have been affected. Therefore, the half-hour return has not yet reached the average level. Nevertheless, they are still very uncertain and unpredictable.

The last half-hour returns of stock markets securities can be predicted by the first half-hour returns or the second to last half-hour return. In the form of in-sample analysis, the work of Hou and Li (2013) suggests that both the first half-hour returns, and second-to-last half hour returns can successfully forecast the last half-hour return in the stock markets of a leading economy, showing a significant positive regression slope. This makes highly predictive as it is much greater than 1%. Moreover, especially in the US stock markets, the simultaneous application of these two predictors to predict accurate half-hour returns gives a remarkable , which is much higher than that of other stock markets across the world (Coleman & Milanova, 2019). Researchers and practitioners have also observed that in-sample analysis indicates that the first half-hour return, and second-to-last half-hour returns individually produce a higher return on the stock, which is different from half-hour returns in the USA because of other trading behaviors, investors preferences, and trading timing. However, the two momentum indicators, the first and the second-to-last half-hour returns, provide complementary information to traders and investors in making effective investment decisions in both countries' stock markets (Basdekidou, 2017).

Likewise, Elaut et al. (2018) addresses the impacts of trading volume and return volatility

on in the stock markets' intraday momentum. In this case, they sort out the given trading days into lower, medium, and higher terciles based on volatility and trading volume analysis of the first half-hour, and then calculate the statistics for each tercile. These studies show that, according to the 'Amihud illiquidity' measure, the given trading days can be divided into high and low groups. Intraday momentum is stronger than the high volatility trading days, mid-volume trading days, and low-liquidity trading days. However, this intraday momentum predictability has been found fluctuant during the prevalence of contagious disease COVID-19 due to the constant uncertainty of the market environment and instability in the stock volume and prices, although the economic activities mostly play a less significant role in the stock market return when compared to the role of intraday momentum (Narayan et al., 2018; Phan & Narayan, 2020). Nevertheless, based on the movement in asset allocation and trading time perspectives, the economic importance of intraday momentum dominates the global stock market returns literature. Furthermore, the investigation of Eross et al. (2019) reveals that the last half-hour predictions based on the current intraday momentum provides significant economic benefits to mean-variance investor allocation among risk-free bills and equities.

In the stock markets where lunch break is allowed for more than one hour, it has been investigated that a half-day momentum, which is beneficial in predicting a stock return. In this regard, the stock markets securities return information collected half a day before the lunch break can help the investors predict the return rate on securities in the afternoon (Nofsinger & Prucyk, 2003). These studies concluded that the half-day predictions of stock returns are economically and statistically important, regardless of whether it shows an increase or a decrease in the predictability of the returns relative to the first half-day. Additionally, the half-hour returns calculation and the half-hour trading market lunch break contain much more helpful information for the predictors. Moreover, literary work findings, such as Schulmeister (2009) explains that the intraday momentum of the stock markets is influenced by investor trading behaviors, and investor periodically analyze and rebalance their investment portfolios because light moves capital. Investors with the late information and slow processing and trade

near to market's closing price will calculate the value of their assets (mutual funds), calculate the returns of their portfolios, and try to avoid overnight risks. These studies show a U-shape in the high trading volume concentrating on the stock markets' first and last half-hours. Easley et al. (1997) mentioned that the first return hour is a good relationship with an opening hour in three markets, such as *Tokyo, London, and New York*. We also found that on Monday morning after the weekly holiday, the stock market was running smoothly for the first half-hour. Intraday momentum has been extensively studied in the academic literature, as seen in the initial literature review. The strategy developed by de Bondt and Thaler (1985) in discriminating between loser and winner portfolios based on low-frequency data has been adopted in most previous investigations (monthly, weekly, or daily).

2. Data and Intraday Momentum Methodology

For the half-hour intraday return, we used the two countries' historical index database. The S&P500 from paid sources (firststratedata.com) and the CSI300 from the Shanghai Composite Index (joinquant.com) are extracted from the sample period from January 1, 2020, to September 11, 2020. Our database period has a short and in-sample because the stock markets were mainly affected by COVID-19 in that time; besides, both the stock markets are shocked, volatile, and uncertain.

In S&P500 index details use the first half-hour re-entry was reviewed using the previous closing price from 16:00 to 10:00 on Eastern Time and then every half hour starting at 09:30 to 16:00 on Eastern Time. The second half-hour re-entry from 10:00 to 16:00 on Eastern Time and a total of 13 half hours of period calculated per day.

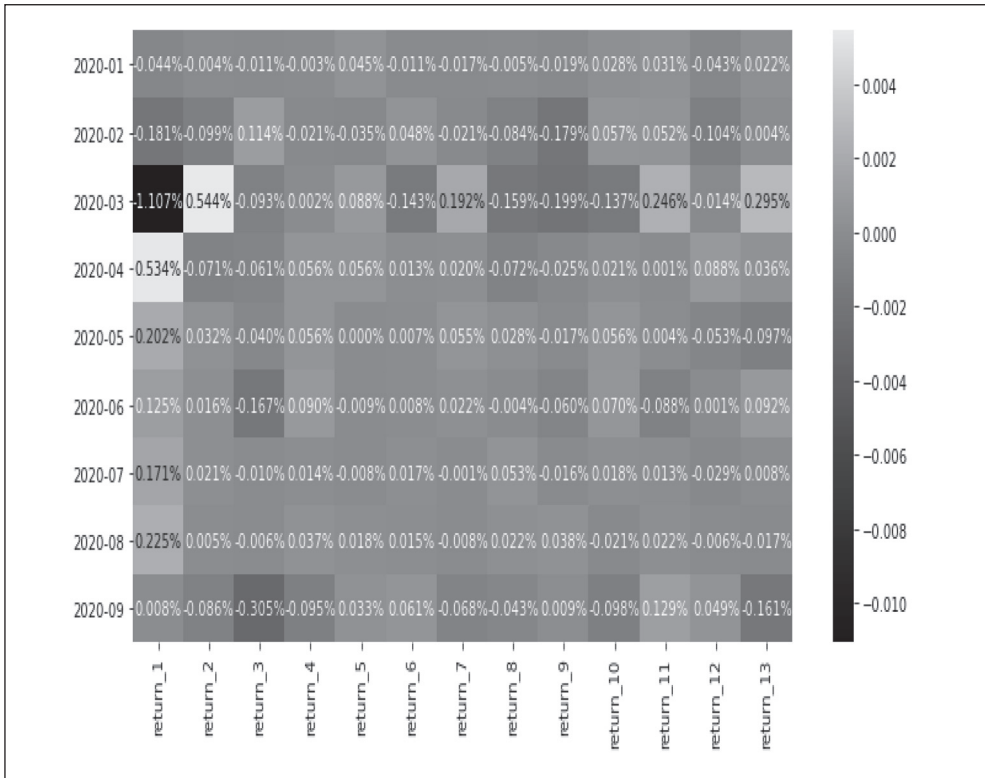
$$IMreturn_{s,t} = \frac{p_{s,t}}{p_{s-1,t}} - 1, \quad s = 1, \dots, 13 \quad (1)$$

$$IMreturn_{s,t} = \frac{p_{s,t}}{p_{s-1,t}} - 1, \quad s = 1, \dots, 8 \quad (2)$$

Here $IMreturn_{s,t}$ is the price at s^{th} half hour, and $p_{s-1,t}$ is the previous half-hour price, for $s = 1 \dots$, formula (1) S&P500 for 13 and formula (2) CSI300 for 8.

Here the CSI300 data calculation is the same as S&P500 data. We only change the time interval, because the total trading time

Fig. 1: Intraday momentum on stock return in COVID-19 situation S&P500



Source: own explanation based on intraday data estimate results

of CSI stock market in a day is 4 hours, with a total of 240 observations, and the daily S&P500 stock trading time is 6.5 hours, with a total of 390 observations. Also, the CSI300 stock market closed at 15:00. The S&P500 and CSI300 return pattern is shown in (Fig. 1 and 2).

For S&P500 & CSI300 Stock Market Index data, the following two formulas:

$$s\&p500IMreturn_{13,t} = \alpha + \beta_{s\&p500IMreturn_{1,t}} + \beta_{s\&p500IMreturn_{12,t}} + \epsilon_t \quad s = 1 \dots, T \quad (3)$$

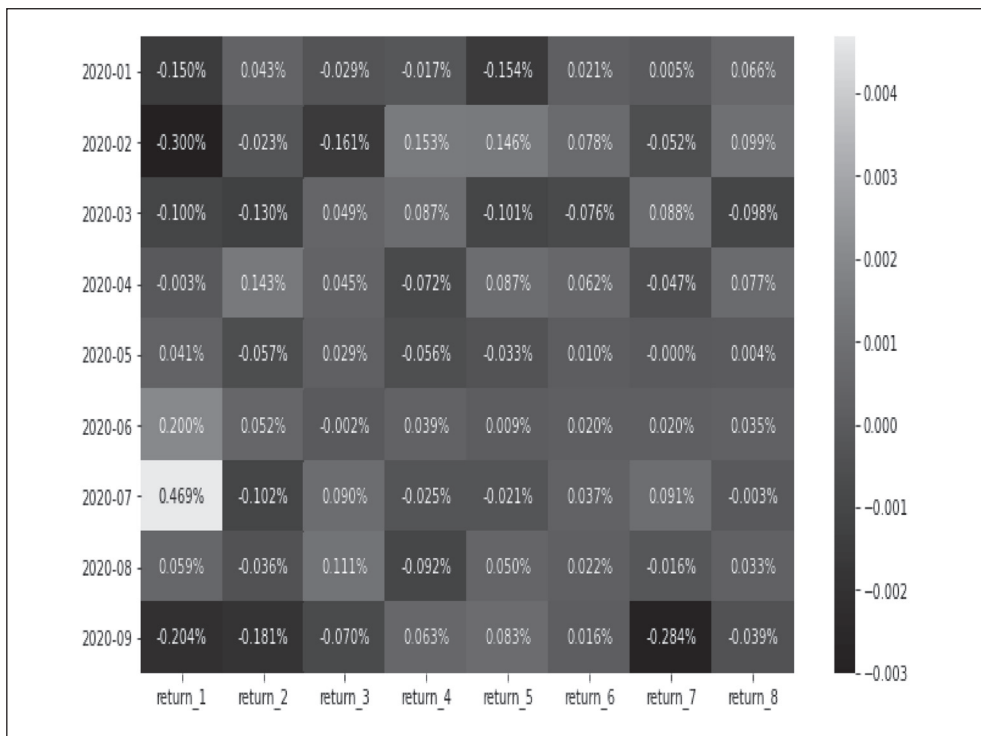
$$csi300IMreturn_{8,t} = \alpha + \beta_{csi300IMreturn_{1,t}} + \beta_{csi300IMreturn_{7,t}} + \epsilon_t \quad s = 1 \dots, T \quad (4)$$

Here, the $s\&p500IMreturn_{13}$ & $csi300IMreturn_{8}$ intraday momentum return on the dependent variable for the USA market and China market, respectively. $\beta_{s\&p500IMreturn_{1,t}}$, $\beta_{s\&p500IMreturn_{12,t}}$

and $\beta_{csi300IMreturn_{1,t}}$, $\beta_{csi300IMreturn_{7,t}}$ are intraday momentum returns on the independent variable for USA and China market respectively, and ϵ_t = Error term.

This study has employed the OLS regression approach to record a single response variable on at least one interval scale. Hutcheson (2011) suggests that the most popular OLS regression statistical technique is to use predict the value of continuous response variable using one or more explanatory variables and identify the relationship's strength. The present study also indicates the returns of a single response variable recorded on an interval scale. In addition, in comparative studies, OLS is regarded as the best estimation technique (Lee, 2002). The OLS regression is one of the most commonly used mathematical methods to forecast the value of continuous response

Fig. 2: Intraday momentum on stock return in COVID-19 situation CSI300



Source: own explanation based on intraday data estimate results

variable with more explanatory variables. This analysis also predicts the intensity of the interaction between these variables with a single interval scale response.

Generally, we follow the method by Gao et al. (2018) predictive regression model in-sample of the stock market's intraday momentum. The in-sample intraday momentum predictive regression models of S&P500 are mentioned in formulas (5), (6), and (7).

$$s\&p500IMreturn_{13,t} = \alpha + \beta_{s\&p500IMreturn_{1,t}} + \epsilon_t \quad s = 1 \dots, T \quad (5)$$

$$s\&p500IMreturn_{13,t} = \alpha + \beta_{s\&p500IMreturn_{12,t}} + \epsilon_t \quad s = 1 \dots, T \quad (6)$$

$$s\&p500IMreturn_{13,t} = \alpha + \beta_{s\&p500IMreturn_{1,t}} + \beta_{s\&p500IMreturn_{12,t}} + \epsilon_t \quad s = 1 \dots, T \quad (7)$$

where $s\&p500IMreturn_{13,t}$ is the last half-hour return and $s\&p500IMreturn_{1,t}$ is the first half-

hour return, and $s\&p500IMreturn_{12,t}$ is the second last (12) half-hour return, t is the trading day, and Error term ϵ_t with a mean equal to zero.

The predictive regression model in-sample data of the intraday momentum CSI300 in formulas (8), (9), and (10).

$$csi300IMreturn_{8,t} = \alpha + \beta_{csi300IMreturn_{1,t}} + \epsilon_t \quad s = 1 \dots, T \quad (8)$$

$$csi300IMreturn_{8,t} = \alpha + \beta_{csi300IMreturn_{7,t}} + \epsilon_t \quad s = 1 \dots, T \quad (9)$$

$$csi300IMreturn_{8,t} = \alpha + \beta_{csi300IMreturn_{1,t}} + \beta_{csi300IMreturn_{7,t}} + \epsilon_t \quad s = 1 \dots, T \quad (10)$$

where $csi300IMreturn_{8,t}$ is the last half-hour return and $csi300IMreturn_{1,t}$ is the first half-hour return, and $csi300IMreturn_{12,t}$ is the second last (7) half-hour return, t is the trading day and Error term ϵ_t with mean equal to zero.

Mathematically, we follow the Gao et al. (2018) technique using the first half-hour signal $IMreturn_t$, trading signal based on last half-hour return on day t . If the time signal is positive, we will take a long position; otherwise, we will close the market each trading day. The conditional movement follows in formulas (11) and (12).

$$S\&P500: n^{(IMreturn_1)} = \begin{cases} IMreturn_{13}, & \text{if } IMreturn_1 > 0; \\ -IMreturn_{13}, & \text{if } IMreturn_1 \leq 0 \end{cases}$$

$$CSI300: n^{(IMreturn_1)} = \begin{cases} IMreturn_8, & \text{if } IMreturn_1 > 0; \\ -IMreturn_8, & \text{if } IMreturn_1 \leq 0 \end{cases}$$

We will stay or out it depends on mathematically return when we use both the trading signal $IMreturn_1$ and $IMreturn_{12}$; $IMreturn_1$ and $IMreturn_7$, if all returns are positive, we should go long position otherwise short position. Mathematically, the return is calculated as follows:

$$S\&P500: n^{(IMreturn_1, IMreturn_{12})} = \begin{cases} IMreturn_{13}, & \text{if } IMreturn_1 > 0 \text{ and } IMreturn_{12} \leq 0; \\ -IMreturn_{13}, & \text{if } IMreturn_1 \leq 0 \text{ and } IMreturn_{12} \leq 0; \\ 0, & \text{Otherwise.} \end{cases}$$

$$CSI300: n^{(IMreturn_1, IMreturn_7)} = \begin{cases} IMreturn_8, & \text{if } IMreturn_1 > 0 \text{ and } IMreturn_7 \leq 0; \\ -IMreturn_8, & \text{if } IMreturn_1 \leq 0 \text{ and } IMreturn_7 \leq 0; \\ 0, & \text{Otherwise.} \end{cases}$$

Finally, Newey and West (1987) *Robust t-statistics* is used here for all regression model cases, and the significant level is at 1%, 5%, or 10% as marked with ***, ** or *.

3. Empirical Results

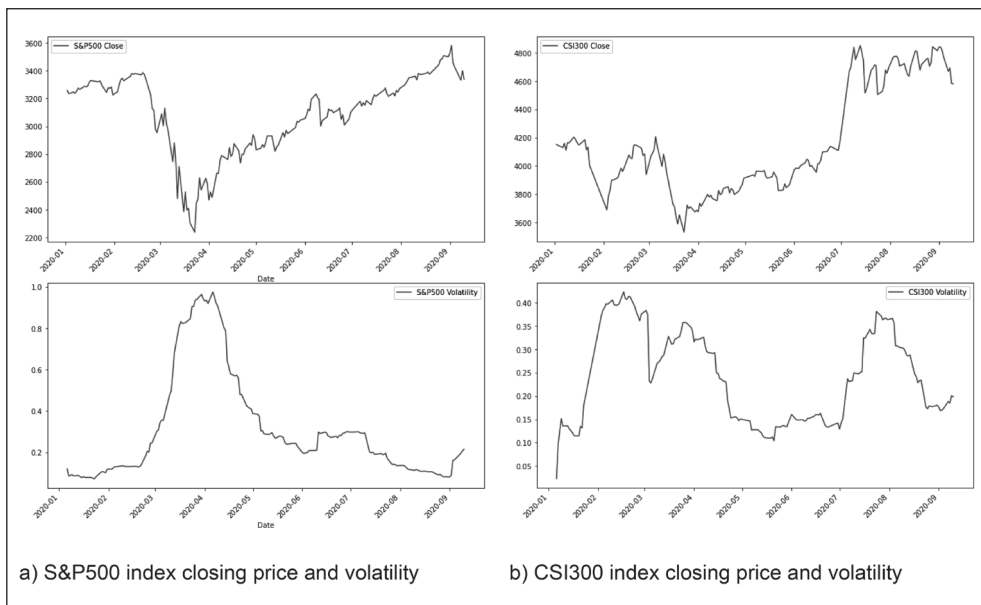
Statistically, sample studies provide evidence of intraday patterns, which helps to consider the economic factors behind this process. We also studied the U-shape of the financial market transaction volume and price levels. Jain and Joh (1988) demonstrated that the plot will perfectly show that it is consistent with earlier intraday findings; the pattern is stronger on high-volatility days; trading size highly impacts when volatility rises. The U-shape pattern suggests that the new information from the first half-hour to the last half hour decides to avoid overnight risk.

In this article, we split the overall market hours by half an hour, concentrate on the half-hour return from the end of the day, and significantly predict the last half-hour return. We are also curious why the first half-hour and last half hour are related to investors. When the market opened, the positive impact on the new information was different from other days. Therefore, the volatility and trading volume in the last half hour are relatively high, actual trading volume, return and volatility follow U-shaped patterns. According to Gao et al. (2018), and Rapach and Zhou (2013), the transaction volume of the first half-hour and the

last half-hour is typically U-shaped, and the data is significant. increases significantly besides sample signs the time predictability. We focus on returns in the first and last half-hour; also, the closing price and volatility of the S&P500 and CSI300 day factor trends are shown in the following Fig. 3.

From an economic point of view, the economic factors behind this illusion are also taken into consideration. Bogouslavsky (2016) suggests that unusual portfolio re-equilibrium is the driving force of the economy. Murphy and Thirumalai (2017) shows that they provide real evidence that the organization has implemented repeated instructions, demonstrating that they seldom rebalance. Bogouslavsky (2016) uses unusual re-equilibrium to describe autocorrelation and seasonal returns. This suggests that intraday impulse may potentially guide investors who delay to re-equilibrium their business to close the market instead of opening the markets. The trading shifts intuitively in the same direction as the first half-hour and creates a strong connection between the two returns.

The second theory is the participation of late-informed investors. As soon as the good news published, some investment companies

Fig. 3: Factor volatility and closing price in COVID-19 situation S&P500 and CSI300

Source: own explanation based on intraday stock markets data

immediately purchase, driving the market in the first half-hour. Others will discover the news later, or simply absorb the news too gently in the first half-hour. Baker and Wurgler (2006) found that information can be transferred across some industries for up to one month, and Cohen and Frazzini (2008) and Hong et al. (2007) pointed out that investors continue to measure month-old sentiment. Thus, it may take an entire day to process information. Their trading method is the same as the actual income of the first half-hour produced during the last half hour, thus creating a natural correlation.

Some mutual funds tend to sell close to the closing price because this is desirable for day-to-day adjustment and the use of analytical factor models that focus on closing costs. Besides, investors in mutual funds can only trade at the closing price. Rationally, the fund managers are recommended to sell close to the market to hold the value of the waiting option. Technically, they can also be called 'late-informed' as their trading time is earlier than this day. Overall, these are two reasons that can provide economic justification for clear statistical proof of intraday vitality. Other theories for this progressive general equality

model for intraday motive comprehension, risk producers, and the intraday predictability balance prize are needed for future research.

3.1 Market Prediction in COVID-19 Situation

In-sample Regression

Formulas (5), (6), and (7) follow the market prediction of S&P500 under COVID-19. In formula (5), this study reports that the findings of the analysis of the S&P500 index first half-hour $\beta_{1Mreturn_1}$ is a positive slope, which statistically 10% significant with R^2 is (0.048). In contrast, in formula (6), the positive slope in the first half-hour is too low with insignificant upper 10% and last half-hour also $\beta_{1Mreturn_{1,2}}$ is a negative slope with insignificant upper 10%, and R^2 is (0.000). In formula (7), when we predict both return together, R^2 is a positive slope (0.057), with a statistical significance level of 5%, and ensures that in case of COVID-19, half-hour can be predicted, but $\beta_{1Mreturn_{1,2}}$ has no intraday momentum effect in the second to last half hour (see Tab. 1: A). In conclusion, the in-sample results existing the intraday momentum

Tab. 1: Market estimation of the S&P500 & CSI300

	S&P500 (Panel A)			CSI300 (Panel B)		
	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$
$\beta_{IMreturn_1}$	0.102*		0.119**			
	(1.64)		(2.00)			
$\beta_{IMreturn_{12}}$		-0.0384	-0.219			
		(-0.11)	(-0.76)			
$\beta_{IMreturn_1}$				0.0207		0.0203
				(0.84)		(0.81)
$\beta_{IMreturn_7}$					0.118	0.118
					(1.31)	(1.29)
_cons	0.000376	0.000358	0.000344	0.000206	0.000213	0.000208
	(0.66)	(0.62)	(0.61)	(0.82)	(0.85)	(0.83)
\mathcal{R}^2	0.048	0.000	0.057	0.005	0.017	0.022

Source: own

Note: Robust t-statistics found in parenthesis and the significant level is at 1%, 5%, and 10% as marked with ***, **, and * respectively.

$IMreturn_{13}$ to $IMreturn_1$, but no intraday effect between $IMreturn_1$ to $IMreturn_{12}$.

Formulas (8), (9), and (10) follow the CSI300 market prediction under the COVID-19 situation. In formula (8), this study reports that the positive slope of $\beta_{IMreturn_1}$ in the first half-hour of CSI300 index positive slope too low and statistically significant with \mathcal{R}^2 is 0.005. In contrast, in formula (9), the first half-hour is too low and not significant, and the last half-hour $\beta_{IMreturn_{12}}$ is also a negative slope, not statistically significant, \mathcal{R}^2 is 0.017. In formula (10), when we jointly predict that both will return together, \mathcal{R}^2 is a positive slope (0.022), and ensure that during COVID-19, it can be predicted for the first half-hour, but there is no intraday momentum effect second to last half hour $\beta_{IMreturn_{12}}$ (see Tab 1: B).

The analysis reveals that during the COVID-19 period, intraday momentum does not always exist in both of the markets' first half-hour and last half-hour return. Due to so

much uncertainty of the investors, stock market volatility is unpredictable; this is the reason why it was big shocks in the month of April in the sample database, which is indicated in Fig. 3.

3.2 Diagnostics Test

This study used diagnostics tests such as heteroscedasticity, serial correlation, and normality checks. Because, heteroscedasticity is a systematic change that spans the residual error within a measurement range. If this problem is present in the data, then the estimated t-statistic and F-statistic will be invalid. Serial correlation means when the errors of the different periods are connected. In time series data, serial correlation occurs when the error is related to this time and carried to the future. If we talk about the first-order serial correlation, the error of the current time will correlate to the future time. If we talk about positive serial correlation, the error of the current time is positively related to the future time. The

Tab. 2: Diagnostic tests

Diagnostic tests	S&P500	CSI300
	P-value	P-value
Skewness/Kurtosis tests for normality	0.0000	0.0167
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity	0.0019	0.0000
Breusch-Godfrey LM test for autocorrelation	0.2825	0.7521

Source: own

occurrence of serial correlation also influences the results. In addition to statistics, traditional tests are also used to determine a data set is modelled according to a conventional distribution and measure the likely of its natural distribution based on random variables. The insignificant p-value (reported in Tab. 2) indicates that there is no problem with heteroscedasticity and serial correlation in the study models.

3.3 Market Timing and Conditional Predictability

The present study uses market timing value as a predictive indicator, that is, the first half-hour to second last half-hour timing signal. In general, the market takes a long position if the last half-hour signal is positive and a short position when the signal is negative. As far as our study on COVID-19 is concerned, we cannot take a long position; therefore we need to consider our risk measures. Ito and Hashimoto (2006) examines the effect of the opening hour on stock market and test the significance of dummy variables, however, mostly on Monday morning. Generally, when the first half-hour return is positive and negative, there are two types of explanations for stronger and weaker predictability. First, if the stock behavior effect, investors need to hold the stock and sell the last half hour on bad news; second, with asymmetric cost (Coval & Shumway, 2005; Locke & Mann, 2005; Odean, 1998). Ito and Hashimoto (2006) shows that conditional on negative past returns is stronger than positive past return in the intraday cross-sectional momentum. Due to the disposition effect, investors and stockholders are reluctant to sell due to the bad news (Haigh & List, 2005; Locke & Mann, 2005). The stockholders are widely distributed by ownership rights in the stock market (Sadaf et al., 2019). Second, due to cost imbalance, arbitrageurs are less induced

to arbitrage in a down market. For example, Abreu and Brunnermeier (2002) argues that arbitrators who receive bad news need to shorten their assets, which is more expensive than good news arbitration. On the other hand, Cushing and Madhavan (2000) proved that people who sold harmful information earlier in the day appeared to cover their market close to cost. When major economic news release we can take two strategies. The first is *Always long strategies*, and the second is *Buy-and-hold strategies*. Gao et al. (2018) recommended the first approach when the market takes a long position beginning to last, close it with market close. But second strategies hold them until the end of the total sample period.

During the COVID-19 sample period, Tab. 3, S&P500 reports that when $IMreturn_1 > 0$ is positive and R^2 for the regressions, which are 0.106, 0.029, and 0.119, respectively. The first half-hour return is positive and significant, and the last half-hour return is negative and insignificant. In contrast, when $IMreturn_1 < 0$ is negative and R^2 are 0.034, 0.029, and 0.108, respectively, we found that the first half-hour return is positive, and the results are insignificant, while the last half-hour return is negative and insignificant. The results suggest that intraday momentum is stronger than other days when the first half-hour returns are positive. The suggested models are given in the following formulas (11) and (12).

$$s\&p500IMreturn_{13,t} = \alpha + \beta_{s\&p500IMreturn_{1,t}} + \beta_{s\&p500IMreturn_{12,t}} + \epsilon_t \quad s = 1 \dots T, \tag{11}$$

where $\beta_{s\&p500IMreturn_{1,t}}$ = First half-hour Positive or Negative Signal return; $\beta_{s\&p500IMreturn_{12,t}}$ = Second last half-hour return based on First half-hour and $s\&p500IMreturn_{13,t}$ = Last half-hour based on first half-hour signal.

Tab. 3: S&P500 first half-hour conditionally positive and negative

S&P500 Stock variables	When $IMreturn_1 > 0$			When $IMreturn_1 < 0$		
	(1)	(2)	(3)	(4)	(5)	(6)
	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$
$IMreturn_1$	0.219** (2.13)		0.205** (2.00)			
$IMreturn_{12}$		0.368 (1.00)	0.253 (0.72)			
$IMreturn_1$				0.102 (0.99)		0.169 (1.60)
$IMreturn_{12}$					-0.358 (-0.67)	-0.622 (-1.48)
_cons	-0.00120* (-1.72)	0.000583 (0.99)	-0.00116 (-1.58)	0.00112 (1.02)	-0.000393 (-0.42)	0.00145 (1.23)
\mathcal{R}^2	0.106	0.029	0.119	0.034	0.029	0.108

Source: own

Note: robust t-statistics found in parenthesis and the significant level is at 1%, 5%, and 10% as marked with ***, **, and * respectively.

Tab. 4: CSI300 first half-hour conditionally positive and negative

CSI300 Stock variables	When $IMreturn_1 > 0$			When $IMreturn_1 < 0$		
	(1)	(2)	(3)	(4)	(5)	(6)
	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$
$IMreturn_1$	0.00723 (0.12)		-0.0158 (-0.24)			
$IMreturn_7$		0.192* (1.68)	0.197 (1.62)			
$IMreturn_1$				0.0244 (0.65)		0.0227 (0.58)
$IMreturn_7$					0.0501 (0.35)	0.0439 (0.30)
_cons	0.000323 (0.64)	0.000464 (1.42)	0.000585 (1.14)	0.000225 (0.53)	0.0000320 (0.08)	0.000193 (0.41)
\mathcal{R}^2	0.000	0.047	0.048	0.005	0.003	0.007

Source: own

Note: robust t-statistics found in parenthesis and the significant level is at 1%, 5%, and 10% as marked with ***, **, and * respectively.

Similarly, Tab. 4, CSI300 reports when $IMreturn_1 > 0$ is positive and R^2 values are 0.000, 0.047, and 0.048, respectively. We found that when the first half-hour signal is positive with insignificant upper 10%, the last half hour is a positive slope with 10% significance. However, it is different from S&P500 conditionally signal method due to COVID-19 shocks and when $IMreturn_1 < 0$ is negative, same as usual S&P500 index.

$$csi300IMreturn_{8,t} = \alpha + \beta_{csi300IMreturn_{1,t}} + \beta_{csi300IMreturn_{7,t}} + \epsilon_t \quad s = 1 \dots T, \quad (12)$$

where similarly, we used in same as the S&P500 index.

3.4 Volatility and Volumes

Between the COVID-19 crisis, we sort all trading days in our sample into three groups

(high, medium and low). We consider the joint prediction first half-hour and second last half-hour returns. Because Gao et al. (2018) and Zhang (2006) suggest that higher volatility prediction is positively significant and uncertain. In addition, the volume also impacts intraday momentum. The necessary behavior of intraday market procedures is trading volume and price volatility, followed by the U-shape. These two variables reach their highest values when the market ups and down. Easley et al. (1997) presented a similar pattern in both stock markets when the opening hours multilateral auction is separated without such a system. Admati and Pfleiderer (1988) mentioned when the transaction costs are smaller and unexpected traders enter the market, it means a 'cluster market' effects. Because at that time, some informed traders enter the market quickly

Tab. 5: S&P500 and CSI300 Volatility and Volume based on First half-hour return

S&P 500 (Panel A)						
Stock variables	Volatility			Volume		
	High	Medium	Low	High	Medium	Low
	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$
$\beta_{IMreturn_1}$	0.155*	0.314	-0.170	0.171**	0.0658	-0.119**
	(1.75)	(0.48)	(-0.99)	(2.35)	(1.56)	(-2.00)
$\beta_{IMreturn_{12}}$	0.332	-0.950**	0.307*	-0.546	0.401***	-0.0644
	(0.70)	(-2.38)	(1.98)	(-1.31)	(2.82)	(-0.40)
Intercept or const	0.00212	-0.00489	0.00249	0.00184	-0.000235	0.0000887
	(1.62)	(-0.52)	(1.31)	(1.16)	(-0.53)	(0.35)
R^2	0.179	0.200	0.070	0.109	0.136	0.111
CSI300 (Panel B)						
Stock variables	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$	$IMreturn_8$
$\beta_{IMreturn_1}$	0.0274	0.0287	-0.00548	0.0897	-0.0134	0.0166
	(0.63)	(0.52)	(-0.15)	(1.64)	(-0.47)	(0.48)
$\beta_{IMreturn_7}$	0.142	0.138	0.0781	0.230	0.0109	0.0532
	(0.74)	(0.88)	(0.62)	(1.47)	(0.09)	(0.38)
Intercept or const	0.0000914	0.000195	0.000384	-0.000301	0.000335	0.000464*
	(0.20)	(0.46)	(0.89)	(-0.50)	(0.88)	(1.70)
R^2	0.034	0.027	0.010	0.097	0.004	0.005

Source: own

Note: robust t-statistics found in parenthesis and the significant level is at 1%, 5%, and 10% as marked with ***, **, and * respectively.

and hide their identity. Due to the leakage of some private information, asset prices fluctuate greatly. That is why there is a strong correlation between volume and volatility, but not at the same time.

Similarly, Lee et al. (1993) pointed out that when higher volatility is associated with leakage of private information, there is a positive relationship between volatility and transaction volume, that time market lead to uncertainty. According to data analysis, we have tried to find out the impact of volatility and trading volume on the pandemic crisis. Because the trading volume has increased and decreased during the COVID-19 period, that is why, the trading volatility and trading volume are divided into three parts based on the first half-hour return; high, medium, and low.

In Tab. 5, Panel A reports the results. When the volatility is high, the first half-hour $IMreturn_1$ (0.314) is significant with at 10% confidence interval level, but the last half hour is insignificant. The medium level volatility is significant 5%, however, the beta coefficient is negative in the second last (12th) half-hour returns. Besides, the low level is also a significant level, with a 10% level in the last (12th) half-hour returns.

Similarly, when the volume is high and low, the first half-hour returns $IMreturn_1$ (0.171** and -0.119^{**}) is significant, however, the beta coefficient relation is positive and negative. The medium level of volume second last (12th) half-hour is at 1% significant level, $IMreturn_{12}$ is 0.401. In contrast, Tab. 5 Panel B reports that the volatility and volume level are insignificant. In formulas (12), (13), and (14), we have found no intraday effect on the CSI300 stock market.

3.5 First Half-hour of Return on Monday Morning

Based on our data from the US market, the first half-hour can predict and prove that the first half-hour data is significant. Easley et al. (1997) pointed out that the first half-hour return is a good relationship with the opening hours of the three markets (Tokyo, London and New York). Easley et al. (1997) also found that the first half-hour is essential for good prediction using the buy hold strategy. We examined that there is no intraday momentum in China's opening market hour, and there is no intraday both of market in the last half-hour. That is why in the COVID-19 situation, we also only examine the first half-hour returns on Monday morning.

Tab. 6: S&P500 and CSI300 First half-hour return on Monday morning

Stock variables	S&P500			CSI300		
	(1)	(2)	(3)	(4)	(5)	(6)
	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$	$IMreturn_{13}$
$IMreturn_1$	0.193***		0.144***			
	(4.11)		(2.87)			
$IMreturn_{12}$		0.867*	0.462			
		(1.91)	(0.97)			
$IMreturn_1$				0.0427		0.0434
				(1.02)		(1.04)
$IMreturn_7$					-0.0681	-0.0783
					(-0.29)	(-0.33)
_cons	0.00109	0.00103	0.00124	0.000194	0.0000292	0.0000984
	(1.12)	(1.09)	(1.36)	(0.30)	(0.04)	(0.14)
\mathcal{R}^2	0.415	0.317	0.478	0.038	0.004	0.043

Source: own

Note: robust t-statistics found in parenthesis and the significant level is at 1%, 5%, and 10% as marked with ***, **, and * respectively.

Because the opening effect of the stock market smoothly works on Monday morning after weekly holidays. Easley et al. (1997) indicated that the trading day may be intensive between two types of buyers and sellers as the exchange of news model information.

Tab. 6: S&P500 reports that the first half-hour is a positive slope (0.193) with 1% significant level and \mathcal{R}^2 is very impressive in COVID-19 period. The last half-hour is also a positive marginal slope (0.867*), with a significant level of 10%, which satisfy the \mathcal{R}^2 (0.317). In addition, the joint prediction is a good position coefficient and \mathcal{R}^2 is 0.478. In contrast, the first half-hour of CSI300 is marginally coefficient (0.0427), but the \mathcal{R}^2 (0.038) position is not well enough; this is why the result is insignificant in this case. And last half-hour slope is negative, and \mathcal{R}^2 is very low. Our studies found that due to COVID-19 shocks, Monday morning is beneficial for S&P500, but CSI300 has no effect on the Monday morning strategy.

4. Discussion

This study represents that when the returns are more optimistic, the data estimation results are often be a positive coefficient. Mazur et al. (2021) pointed out that the US stock markets crash during March 2020 by COVID-19 and market volatility negatively correlated with stock returns. Besides, measured Dow Jones Industrial Average, the market fell by 26%, and the US GDP decreased by 4.8% in the first-time quarter of 2020, and the unemployment rate soared to above 20%. Baker et al. (2020) suggested that government restrictions on commercial activities and voluntary social distancing were the main reason the US stock market reacted to COVID-19 than before in 1918–19, 1957–58, and 1968. Sun and Gao (2020) examined the negative impact on Chinese stock returns. Overall, during COVID-19, it cannot be explained by real losses.

Borgards et al. (2021) found that during the COVID-19 shock, it was profitable for trading returns but could be exploited by traders. Overall, pandemic shocks provide extreme market overreactions behavior, which can be returns positive or negative. According to our significance analysis (e.g., market prediction, market timing and condition), our finding suggests that investors should control the stock price due to market behavior. If the first half-hour return is positive, investors should control

the short position, and the last half hour is negative. Investors should take a long position because intraday momentum is theoretically based on the strategic behavior of informed traders. We also provide another strategy, when volume and volatility are high, investors should take a short position, otherwise a long position. When volatility and volume are high, intraday momentum is stronger than other days (e.g., recession days, economic news). In addition, those interested in investing in minimum risk can be chosen after the weekend first half-hour Monday morning. Because the first half-hour is a good prediction for the stock price and stockholder's mentality affect the positive outlook on trading time, we suggest that the investor take better portfolio management during the pandemic crisis. These findings might be help investors to better anticipated the pandemic crisis.

In contrast, when the returns have a negative impact, the data estimation results are also negative coefficient. This uncertainty is greater volatility in the market for factor movement – for example, bad news, economic crisis, financial crisis, and reduced equity. During COVID-19 period, the market also faced the same situation; the first and last half-hour returns are sometimes significant and positive coefficient. Our empirical result shows that, during COVID-19 period, there is uncertainty in the first and last half hours returns. The stock market in-sample data, there is no intraday positive effect in the last half-hour, however, the first half-hour S&P500 has a positive effect on the stock market. Likewise, the market risk exists in the stock market during the pandemic, but the first half-hour can mostly predict S&P500. Conditionally, we found that during the COVID-19 period, the predictions for the first half-hour S&P500 and the last half hour CSI300 were both good. And, there is no intraday prediction in the last half-hour S&P500 and first half-hour CSI300. When volatility and volume are both high, the return will be positive, and this relationship is very close.

Conclusions

In this paper, we provide evidence of the existence of intraday momentum strategies. Intraday momentum is based on investor behavior and trading activity that occasionally rebalance the portfolio, a trading strategy based on timing signal and benchmark of average

return. The intraday pattern is more robust on days when volatility and volume are high, and it has economic and statistical significance because investors can make money with a better portfolio in a pandemic crisis. In the first half-hour of the trading day, our findings show that the market returns are expected to return in the last half hour. During the COVID-19 period, a comparative study of the intraday results for the US stock market and the Chinese stock market found that the intraday predictability of US stock market in the first half-hour is higher than the intraday predictability of Chinese stock market. Secondly, for the last half-hour returns, the Chinese stock markets are better than the USA stock markets. During COVID-19, the findings suggest that the first half-hour stock market is more profitable than the last half-hour in the USA market, while the second there is no intraday momentum in the last half-hour both of stock markets. Finally, Monday morning's first half-hour is a good prediction for the S&P500 index.

Limitations and Future Directions

There are several limitations in this literary work that must be addressed since these limitations provide more opportunities for future researchers and practitioners. This article uses purposive sampling to collect data, which restricts the generality of the findings. Thus, other sampling techniques are recommended to be applied in the future studies to present new findings or reaffirm these findings with some specific amendments. Also, this literary work uses a single source of data acquisition. Although a complete procedure has been implemented from sorting to the utilization of data including all necessary steps, no bias was found; still, it is recommended that the future authors adopt multiple sources to understand better the intraday momentum index in the stock markets. The use of various sources will assist the authors explore concerned issues more widely. It is also recommended to conduct a longitudinal study for better intraday momentum analysis over longer period. Future studies are recommended to be supported by evidence from more countries' stock markets to contribute to the literature more widely.

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