Market Timing Signals with High-Frequency Finance Data for Practitioners Based on RRV Model and Momentum Effect

Chenyang Yu

***Abstract*—Based on high frequency data, we establish a method to measure the market risk using realized volatility, and study the momentum effect of intraday stock market. In the first part we establish relative realized volatility model to help investors better model and forecast volatility of the stock price by capturing large deviations from the average realized volatility level using the second-level financial data of Russell 1000 Large-Cap Stocks ETF. Next, we divide the trading data of DIA index for nearly 20 years in minute-level into non-crisis period, 2008 financial crisis period and the recent COVID-19 epidemic period. The effect of stock market momentum effect in these special periods is investigated, and the impact of COVID-19 on the stock market is analyzed in detail based on such effect. The results show that the intraday momentum effect will be more obvious in the economic crisis caused by financial system factors similar to the 2008 financial crisis, and in severe public event crises like COVID-19, the effect may reverse due to the digestion of market information and the influence of investor sentiment, but it will still maintain the normal positive momentum effect for part of the time.**

***Index Terms*—High frequency data, realized volatility, intraday momentum effect.**

I. Introduction

Since the discovery of the momentum effect in the stock market, this effect, which describes the relationship between the changing trend of the stock market in a statistical sense and the previous stock trends, has attracted the attention of a large number of researchers. When high frequency trading data becomes available, it contains a large number of small changes in stock market transactions that fluctuate in seconds, then the process followed by the entire asset price can be upgraded to a random time process in continuous dimension, so as to realize the tracking of market activities implied in the small changes in stock prices, and researchers will be able to do better by looking at the tiny changes in stock market asset prices contained in the data recorded in seconds.

This paper mainly studies realized volatility as a reliable indicator to measure market risk under intraday volatility, and its help to investors' timing the market. With the use of high-frequency financial data, investors can better solve the problem that the volatility pattern varies with the sampling frequency through historical trading data, so as to use the real trading data to represent the actual price volatility, and better forecast its future volatility pattern.

Therefore, on the basis of describing realized volatility (RV) as a non-parametric method for volatility description that is well used in high-frequency financial research, we use realized volatility (RV) to model and analyze volatility in intradays, so as to make up for the deficiency of low-frequency data in modeling. However, historical financial high-frequency trading data often has a jump, which can also be captured by a large RV value. Therefore, in order to explain the average change of realized volatility in different years, we introduce the relative realized volatility (RRV) method of Yan [1]. Thus, the bouncing financial market data activities can be modeled and analyzed.

Next, we study the methods on how to better help investors time the market from another perspective: intraday momentum effect based on minute-level trading data. We first verify that the momentum effect pointed out by the study of Gao *et al.* [2] holds true for all half hours in a single trading day on the logarithmic return of the last half hour in a long time range, and use this as a criterion to help investors select their portfolios. Then, considering the deviating effect of severe economic crises on returns, we separately examine the impact of the 2008 financial crisis and the current COVID-19 on financial markets, and explain how to use the intraday momentum effect supported by minute trading data to help investors time the market during these special extreme periods.

II. Literature Review

The stock market momentum effect, as a famous anomaly in financial markets, was first discovered in 1993 by Jegadeesh and Titman [3]. At present, most studies on momentum effect focus on the level of monthly or annual return rate, and few studies focus on intraday momentum effect, especially involving the world under the background of coronavirus pandemics with the analysis of COVID - 19 of high-frequency trading days. The momentum effect is of great significance, not only for the study of major event days under the fluctuations, the market efficiency and the role and function of high-frequency traders, but also the microscopic structure of the market.

The first half hour and the last half hour involved in intraday momentum are important in our study for two main reasons. The first reason comes from the importance of analyzing the behavior of intraday traders. The kind of trading, which is based on advance information and is not market efficient, causes the stock price to change within the first half hour of the trading day. The research results of Shefrin and Statman [4], Odean [5], Locke and Mann [6], Coval and Shumway [7] and Haigh and List [8] all fully show

Manuscript received May 29, 2022; revised August 7, 2022.

Chenyang Yu is with the Jinhe Center for Economic Research, Xi'an Jiaotong University, China (e-mail: yuchenyangxjtu@126.com).

doi: 10.18178/joebm.2022.10.6.724

that investors are less willing to give up the trading opportunity in the last half hour due to the effect of the next day's trading. The second explanation was proposed by Admati and Pfleiderer in 1988 [9]. In general, the trading volume of the stock market shows a U-shaped pattern, with large volume in the first and last half hours, and smaller volume in the middle. Hora [10] found that according to the research on investor preference, the best intervening period is at the opening and after the closing of the market. Due to the relative lack of liquidity in the middle period of the stock market, it is not the best time for investors to choose to get involved. These two explanations account for the significant effects of the first and last half hour in the study of intraday momentum. In our empirical study, we mainly document the relationship between these two half hours and study the changes of the intraday momentum effect represented by them as a result of financial fluctuations.

III. Market Volatility

A. Description of the High-Frequency Financial Data

The data we used in this part is from the Russell 1000 Large-Cap Stocks ETF, which records the price change of the stock in seconds, as well as the volume of the trading volume and the number of trading numbers. The following Fig. 1 reflects the high frequency changes of stock prices on the infamous "Flash Crash" day on May 6, 2010 [11] in the American stock market.

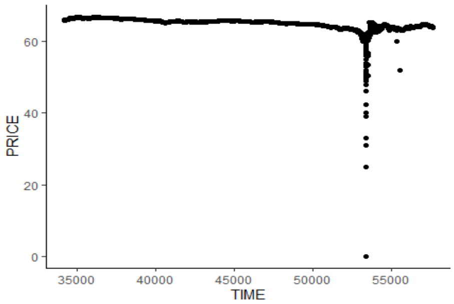

Fig. 1. Stock market crash on the 6th of May 2010.

This figure is a good example of the advantage of high-frequency data on stock prices. At about 2:47 p.m. EDT, the Dow Jones Industrial Average suddenly plunged nearly 1,000 points after a trader typed a wrong letter in a stock sale, mistaking millions (m) for billions (b). Between 2:42 p.m. and 2:47 p.m., the Dow Jones Industrial Average plunged from 10,458 points to 9869.62, down 998.5 points from the previous session's close. By 2:58, the Dow was back at 10479.74. It was the second largest one-day move in the Dow's history. If stock data were of low frequency, they could not capture such detailed changes of stock prices very well.

B. Benefits on Modeling with High-Frequency Financial Data

Another important advantage of high-frequency data is that in quantitative financial research, high-frequency data can make researchers no longer need to be limited by strong econometric assumptions to ensure the rationality of the results. They can directly use the definition of volatility independent of the model itself to describe the fluctuations under different sampling frequencies. In an era when only low-frequency trading data was available, nonparametric methods were not very effective for studying similar continuous time fluctuations. However, using high-frequency data, nonparametric methods are more popular for sampling prices.

Andersen *et al.* [12]-[14] put forward a new method to measure volatility, called Realized Volatility, which is an estimate of realized volatility by summing up the square return of intraday time-sharing data under a certain frequency. The theory proves that this estimator is an unbiased, consistent and effective estimator of the true volatility under the condition that the intraday frequency is properly selected. Therefore, recently a large number of literatures are devoted to the study of non-parametric realized volatility by using high-frequency sample data. The selection of the optimal sample frequency becomes the most critical problem in the process of calculating the actual volatility. If the sample frequency is too small, a consistent estimator of true volatility will not be obtained. If the sample frequency is too large, the measurement result will have a large error because the sum is affected by the market microstructure noise. Realized volatility measurement method is applicable and invariant for different kinds of data collection processes, so this method is very effective for volatility estimation of high-frequency trading data.

Merton [15] proved the following formula with Taylor expansion:

$$\mathrm{E}[RV(t,h,n)] = \frac{b^2}{n} + \sigma^2 \tag{1}$$

and

$$Var[RV(t,h,n)] = 4\frac{b^2\sigma^2}{n^2} + 2\frac{\sigma^4}{n} \tag{2}$$

As n approaches infinity, $RV(t,h,n)$ converges to σ^2, and the variance of $RV(t,h,n)$ approaches 0 [15]. That is, when the sampling frequency is high enough, the realized volatility will be close enough to the true unobserved volatility. However, this conclusion is only reached when the market data is frictionless, that is, there is no noise and no jumps in the price process over a fixed time interval $[t, t+h]$. Therefore, we see that when asset returns are under Brownian motion sampling, the realized return rate is applicable to high-frequency financial data and is effective.

C. Use of Realized Volatility in Describing Intraday Volatility

We now show some results of the intraday volatility observed with high-frequency price data. In this section, we analyze intraday realized volatility as a direct measure of unobserved actual volatility.

We show trading on a typical trading day (September 10, 2014) using data from the Russell 1000 Large-Cap Stocks ETF sampled in seconds on that day. Fig. 2 (a) shows the price change of the day in seconds, Fig. 2 (b) shows the cumulative RV of every time interval of 100 seconds, and Fig.2(c) plots the time series of RV of 100 seconds. Since their numerical dimensions are small, we have multiplied the numerical values of RV by 10^4 to see.

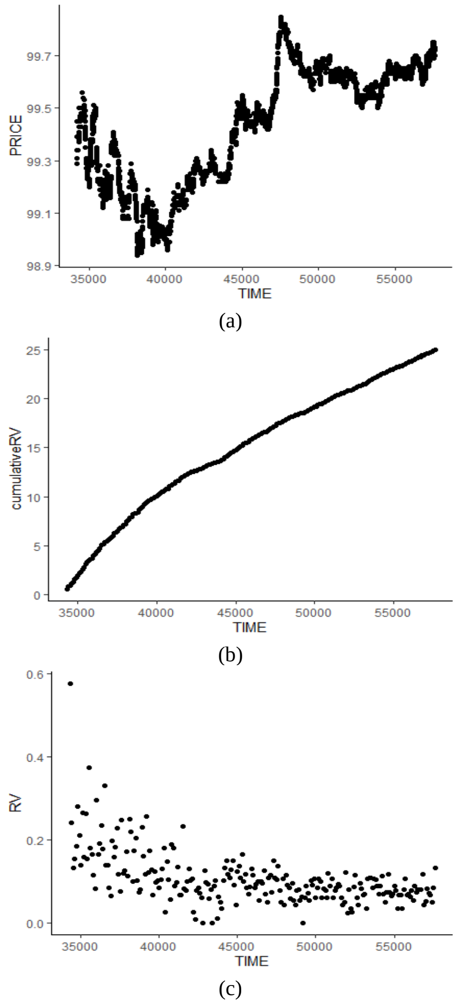

Fig. 2. (a) Price in a typical trading day, Russell 1000 Large-Cap Stocks ETF. (b) Cumulative RV in a typical trading day, Russell 1000 Large-Cap Stocks ETF. (c) RV in a typical trading day, Russell 1000 Large-Cap Stocks ETF.

As can be seen from the figure, first of all, typical stock price volatility is not a random walk volatile process, and the volatility is not a constant. In particular, it can be proved that if the stock price follows the ordinary Brownian motion, then its cumulative volatility in Fig. 2(b) should be a straight line, since RV should be a constant under the random walk model [14], [15]. In addition, the volatility in the 100-second time interval shown in Fig. 2(c) generally shows an overall U-shaped smile curve, but it does not fully explain the dynamic change of volatility. Fig. 2(c) still shows volatility clusters and fluctuations, which are difficult to observe in the process of price change alone.

Since a large deviation of RV from the mean is likely to indicate a jump [16]-[20], it makes sense to empirically test the distribution of intra-day RV over reasonably long (statistically significant) time intervals. This allows us to find outliers of RV that are exceptionally large, which might indicate that jump is occurring.

In order to test the difference of average intraday RV value between different years, Yan [20] established a model called RRV (relative realized volatility) of relative realized return rate, which divides each intraday RV of a time block i by the average RV of the week containing block i. This method can catch large deviations which are likely to be jumps from the average RV level that are not explained by mean reversion or random fluctuations,

Although the theoretical research on the detection of the jump is still very immature due to the difficulty in predicting the arrival time and amplitude of the jump, the empirical studies in the first two parts still give us some clues for modeling the volatility and price.

One of the most recognized approaches is the bi-power and multi-power developed by Barndorff-Nielsen and Shephard [21]. We used the same method to calculate the asset price at time t in the established realized volatility model before, then the multi-power variation (MPV) of X(t) should be:

$$MPV(t,h,n)=\frac{\pi}{2} \bullet \sum_{i=k+1}^{nh}\left\{\left|X(t+\frac{ih}{n},\frac{1}{n})\right|\bullet\left|X(t+\frac{(i-k)h}{n},\frac{1}{n})\right|\right\}^{k} \tag{3}$$

In the above formula, if $k=1$, the formula $BV(t,h,n)$ for calculating Bi-Power (BPV) will be obtained. Unlike RV, which is calculated by summing the square of the returns, BPV is calculated by summing the product of the returns divided by a time interval of length h, thus avoiding the inclusion of large, continuous changes that might include a jump in the aggregate result. Barndorff-Nielsen and Shephard [21] proved that the original formula for realizing volatility as a consistent estimator of the actual volatility of the target,

$$RV(t,h\ ;n)\rightarrow IV(t,h)\ as\ n\rightarrow\infty \tag{4}$$

can be modified to,

$$\lim_{n\to\infty} RV(t,h,n)-BV(t,h,n)=\sum_{t\le s\le t+h} J^2(s) \tag{5}$$

In addition, investors often consider the impact of seasonal effects on stock prices in volatility modeling. Due to cultural habits, holiday arrangement, investment industry practice, securities regulation law and considering the influence of factors such as tax, individual investors in the stock market, large mutual funds, hedge funds as well as a variety of forms such as pension funds will make seasonal positioning, so that the overall stock market trends and individual stock can even show some predictable seasonal characteristics. In the data we studied, however, seasonal effects do not appear in intraday data, except for jumps that may occur at the beginning and end of the trading day. Therefore, the main research point of this paper does not focus on jumps at these special points of time. For future research, researchers can consider introducing a more detailed empirical description of seasonal effects at the intraday level to supplement the research on volatility modeling to capture the jump.

IV. Intraday Return Forecast Ability

In the first section, we mainly studied the use of indicators such as Relative Realized Volatility (RRV) to give investors a better description of volatility, so as to achieve the purpose of timing the market. In this part, as another very useful and widely verified method, we focus on the famous momentum effect in the financial market, and through the verification and analysis of the momentum effect in various aspects, we can better help for investors to time the market.

A. Data

We use historical price data from the SPDR Dow Jones Industrial Average ETF Trust (DIA) over the sample period from January 20, 1998 to June 5, 2020. The data contains the starting price, the final price, the highest and lowest price of each minute, and the number of stocks traded during each single minute when trading occurs. The data contains 2,347,198 pieces of slots of trading information in minutes when trading behavior occurs. We will take the last stock price in the minute to represent the value of the stock at that minute. For the dates in the sample that were too small to calculate the half-hour rate of return, we deleted them to facilitate subsequent analysis.

Then we give our formula for calculating half-hour returns. In order to test the intraday return predictability in any trading day t, we divide the trading period from 9:30 to 16:00 in the trading day into half hours, and get 13 half hours of trading period. Then, the logarithmic return rate of any half hour is:

$$r_{j,t} = \log p_{j,t} - \log p_{j-1,t},\ j = 1,\cdots,13, \qquad (6)$$

where, Pjt is the price at the Jth half hour, while P(j-1)t is the price at the end of the previous half hour, that is, the price at the beginning of the Jth half hour. And P0, t represents the opening price of the day after the trading begins, that is, the initial price of the day. In this way, we are ready to analyze the effect of intraday momentum.

B. Intraday Regression Analysis

In this part, we first use the historical price data of SPDR Dow Jones Industrial Average ETF Trust (DIA) to further verify the intraday momentum effect proposed by Gao *et al.*'s work from the perspective of minute data. We consider the regression equation of the return of the first half hour to the last half hour in the full sample:

$$r_{13,t} = \alpha + \beta r_{1,t} + \varepsilon_t, t = 1,\cdots,T, \qquad (7)$$

In this formula, what the data span T contains is all the data in the sample, namely the remaining minute trading data from January 20, 1998 to June 5, 2020 after excluding the data that cannot be calculated for the return rate. Our results are shown in the Table I below:

TABLE I: REGRESSION RESULTS OF THE FULL SAMPLE

Predictor	r_1
β_{r_1}	0.34***
Adjusted R^2	2.06%
t-value	10.895

The regression results show that the return rate of the first half hour positively influences the return rate of the last half hour, with the influence coefficient as high as 0.34, which is significant at the significance level of 1%.At the same time, the reported adjusted R-square value is 2.06%, which is at a high level. At the same time, the regression result of the R-square value of the full sample obtained by us is very close to Gao *et al.*'s work, which further verifies the reliability and robustness of the research conclusion of the intraday momentum effect. Next, different from the research direction of Gao *et al.*'s work, we investigate the regression analysis of the return rate of each half hour in the whole trading period to the return rate of last half hour, so as to make full use of the trading data of every minute in the sample. We investigate the help of intraday momentum effect based on minute trading data for investors' timing the market, in order to help them make better investment decisions.

The regression equation we adopted is as follows:

$$r_{13,t} = \alpha + \beta r_{j,t} + \varepsilon_t, t = 1,\cdots,T;\ j = 1,2,\cdots,12 \qquad (8)$$

That is, we use the half hours from the first to the twelfth in the trading day as predictors, to predict the logarithmic return of the last half hour in the in-sample trading time. The results of the full sample regression analysis are shown in the Table II below:

TABLE II: REGRESSION RESULTS OF ALL HALF HOURS ON THE LAST HALF HOUR

Predictor	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}
β_{r_i}	0.34***	0.62***	0.93***	1.03***	0.84***	0.79***	0.50***	0.84***	0.71***	0.99***	0.99***	1.03***
Adjusted R^2	2.06%	5.18%	9.47%	8.88%	4.94%	3.85%	1.62%	4.39%	3.43%	8.54%	9.60%	14.54%
t-value	10.895	17.497	24.200	23.360	17.069	15.005	9.656	16.05	14.141	22.881	24.385	30.857

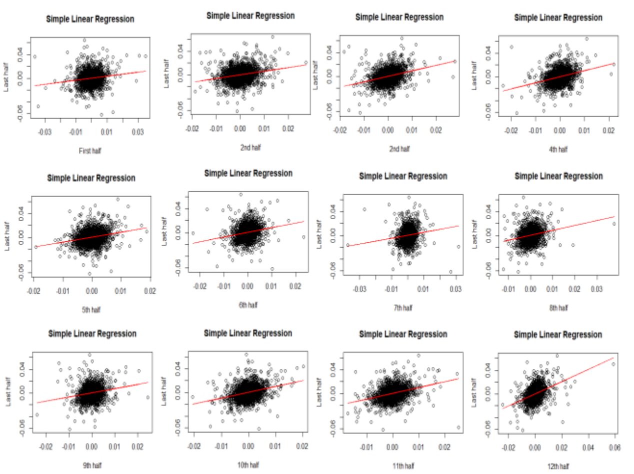

Fig. 3. Regression figures of all the half hours on the last half.

By looking at the reported statistics in full sample, we find that almost all half-hour log returns within the trading period have a significant positive effect on the last half-hour log returns within the trading period. For the adjusted R-square, most half-hour logarithmic returns have an effect on the last half-hour logarithmic returns of 2%-10%, among which the adjusted R-square of some half-hour returns may be higher and the corresponding β value may also be higher. Among them, the penultimate half-hour rate of return shows high β and R-square values, which are much higher than other half-hour coefficient values. That's because the second-to-last half hour, as a predictor, is close enough to the dependent variable -- the last half hour -- that we have reason to believe that the DIA average, which is used as the industrial average at the end of the day, will not move widely over a short period of time. So the yield in the second last half hour has a greater effect on the yield of the last half hour than any other half hour.

It can be seen that, based on the trading data of the whole minute, we draw the conclusion that the intraday momentum effect has a significant effect on the last half hours in different half hour periods of the whole trading day. This holds true for minute-level trading data from January 20, 1998 to June 5, 2020. However, we do know that there are significant large economic fluctuations occurring during this time period that can have a significant impact on the logarithmic returns calculated in our study. Therefore, the whole intraday momentum effect may contain different information in different periods of time, and there could exist a more serious deviation effect. So, it is also necessary to separate the economic periods in which these returns are in to capture relatively persistent outliers and study the impact of momentum effect of intraday minute-level trading data on investors' timing the market. It is also helpful for us to better understand the influence of changes caused by the half-hour return rate on the investor's behavior in the special economic fluctuation cycle, as well as the special fluctuation pattern of the stock trend reflected in the trading data.

Therefore, we examine the intraday momentum effect in each particular period. Within the time range of the whole sample data (from January 20, 1998 to June 5, 2020), there are two economic crises that have great impact on macro economy and the stock market. One was the 2008 global financial crisis from October 1, 2007 to March 31, 2009, which caused the U.S. stock market to fall by nearly 50%. The other was the global COVID-19 crisis from January 1, 2020, to June 5, 2020 (the period when data are available), during which the U.S. stock market experienced a historic plunge of four trading halts in a two-week period. We analyzed the regression results from the first half hour to the last half hour in two special periods, and compared them with the regression results of other periods excluding these two periods, and obtained the regression analysis results as shown in the Table III below:

TABLE III: REGRESSION RESULTS EXCLUDING TWO EXTREME PERIODS

Predictor	$r_{noncrisis}$	$r_{2008crisis}$	$r_{covidcrisis}$
β_{r1}	0.21***	1.07***	-0.42*
Adjusted R^2	0.85%	17.06%	2.00%
t-value	6.69	8.828	-1.784

It can be seen that during the 2008 financial crisis, the market behind the trading data in minutes showed a stronger result of intraday momentum effect. The β coefficient and the adjusted R square value given were as high as 1.07 and 17.06% respectively, and were significant at the significance level of 1%. This proves that in this period of subprime crisis, intraday momentum effect showed a more powerful forecasting effect and can better help investors to time the market. Therefore, when investors choose the underlying assets to invest in, they can take the previous return performance of the underlying asset price and rate of return as an important reference to assist in predicting its future return trend. However, in the recent global COVID-19 crisis, the cause of which is different from that of the 2008 subprime crisis. The economic crisis caused by the outbreak of COVID-19 in early 2020 is completely out of market expectation, and the development trend and changing condition of the epidemic are almost in an unpredictable range, so it is difficult for the market to fully absorb the development trend of the epidemic and make rational investment decisions. At the same time, the economic impact of a public health event like COVID-19 varies from industry to industry. As a result, it is difficult to judge from a fundamental perspective how the intraday momentum results will be based on minute data at this time, when the epidemic has a different impact on the whole industry. Through the regression analysis of the data, we find that the momentum effect presented an adverse effect, that is, the β coefficient value was negative.

The research of Jiang Hai, Wu Wenyang, Wei Shiwei *et al*. [22] pointed out that sudden events similar to COVID-19 would produce unexpected abnormal disturbances to stock returns and the liquidity of the stock market, thus having a huge impact on the stock market. Such shocks are major sudden events. The study of Lasfer *et al.* [23] pointed out that under such events, abnormal oscillatory "overreaction" could easily occur in a short period of time. On the other hand, an emergency like COVID-19 is also prone to a spike in market panic, which further increases market volatility and leads to a sharp rise in market uncertainty. VIX rose rapidly from around 15.56 on February 20, 2020 to 54.46 on March 9. At this point, the United States is not doing much to prevent and control COVID-19.The Federal Reserve started an unconventional rate cut on March 3, 2020, reducing the federal funds target rate by 0.5 percentage points. The move was intended to deal with the epidemic, but it was mainly aimed at financing costs and the market was facing liquidity problems, which made the policy ineffective. Pessimism accelerated after the unconventional rate cuts failed to produce significant results, with the VIX soaring to 82.69 on March 16, the highest since 1900. Meanwhile, the ABC News Consumer Confidence Index has dropped significantly since late February, from 65.6 in the third week of February to 62.7 in the second week of March. Consumption is the main driver of the US economy, and the impact of the epidemic on consumption also means a major impact on the real economy. The impact of the epidemic on economic fundamentals will be transmitted to the financial markets and cause liquidity strains.

V. COVID-19 AND ITS IMPACT ON TIMING THE MARKET

Major public emergencies often have more serious and unexpected disastrous impact on the stock market. The last public health event was the SARS epidemic in 2003. According to the Asian Development Bank, an outbreak of SARS in 2003 cost the Chinese economy $17.9 billion, or 1.3 percent of GDP that year.

The COVID-19 outbreak affected the economy from the demand end to the supply end of all aspects, and made small and medium-sized enterprises face survival crisis. The most immediate impact of the epidemic is the psychological effect of the epidemic, the socio-economic impact through public mood swings. Some of the panic buying that occurred during SARS in 2003 and during the current outbreak was panic-induced. There were only a few hundred confirmed cases and 38 deaths in the United States and Canada, but public fears caused people to overestimate the probability of infection, and the panic cost Canada about C $1 billion.

In view of the correlation between investor sentiment and stock price, more and more studies have begun to pay attention to the impact of major public health emergencies on the stock market through emotional changes. They have all found that emergencies lead to individual emotional and psychological changes, resulting in stock price fluctuations.

Smith [24] summarized the epidemic characteristics of diseases that are prone to public mood swings, such as the emergence, high infectivity and fatality rate of the disease, uncertainty of transmission mechanism and limited treatment means. The COVID-19 epidemic satisfies all the above characteristics and meets the conditions for causing public mood swings. Behavioral finance points out that investors are not completely rational, and their behavior will be affected by emotional and psychological factors. When individuals are in a negative mood, compared with those in a positive or neutral mood state, their risk preference is obviously conservative, and they are less willing to hold stocks and tend to sell stocks. When there is a lot of selling, the share price then falls.

From a realistic empirical perspective, since the outbreak of COVID-19, the trend of major global stock market indexes can roughly reflect the impact of COVID-19 on stock market risks. Data show that from January 15, 2020 to April 1, 2020, the Dow Jones Index in the United States had the largest cumulative decline of 38.4%, and there were 4 circuit breakers in 10 days. The circuit breaker triggered a global stock market shock and ended an 11-year bull run in U.S. stocks that began in 2009. Germany's DAX index fell by as much as 40.3 percent and Britain's FTSE 100 fell by as much as 36.3 percent. In addition, Italy, France, Japan and other countries around the world stock markets also fell sharply. For China, during the same period, China's Shanghai Composite Index fell by the maximum of 18%, with 1,000 shares falling by the limit.

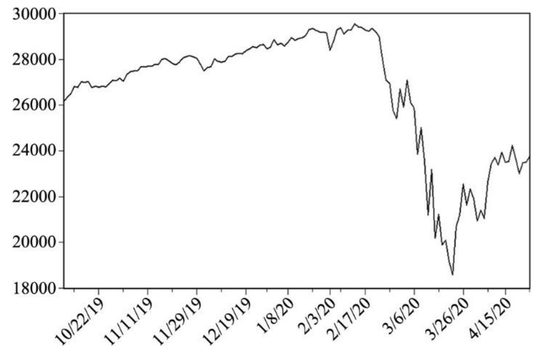

Fig. 4. Stock market changes due to COVID-19.

It can be seen that COVID-19 has a negative impact on the stock market, which is highly volatile and unpredictable due to the lack of market expectations on the future development trend of COVID-19 and the policy changes of the Federal Reserve. This presents a certain challenge to our Time the Market.

We first use the minute-level data to analyze the intraday momentum effect in the whole sample during the COVID period. At this time, the regression equation adopted by us is consistent with the equation used in the second part, except that the data of the sample is collected from January 1, 2020 to June 5, 2020 globally. The analysis results obtained are shown in the following Table IV:

TABLE IV: REGRESSION RESULTS OF ALL HALF HOURS ON THE LAST HALF DURING COVID PERIOD

Predictor	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}
β_{ri}	-0.42 (0.23)	1.13 (0.26)	1.23 (0.29)	1.36 (0.22)	0.16 (0.47)	1.23 (0.39)	-0.31	0.56	1.52	1.63	-0.02	1.22
Adjusted R^2	2.00%	14.54%	13.30%	26.26%	-0.83%	7.56%	-0.0002%	0.63%	40.32%	15.06%	-0.94%	9.82%
Constant	-0.0007 (0.0015)	-0.001 (0.0014)	-0.00009 (0.0014)	-0.0007 (0.0013)	-0.0004 (0.0016)	-0.00002 (0.0015)	-0.0002 (0.0016)	-0.0001 (0.0016)	0.0005 (0.0015)	-0.0001 (0.0014)	-0.0004 (0.0016)	0.000075 (0.0015))

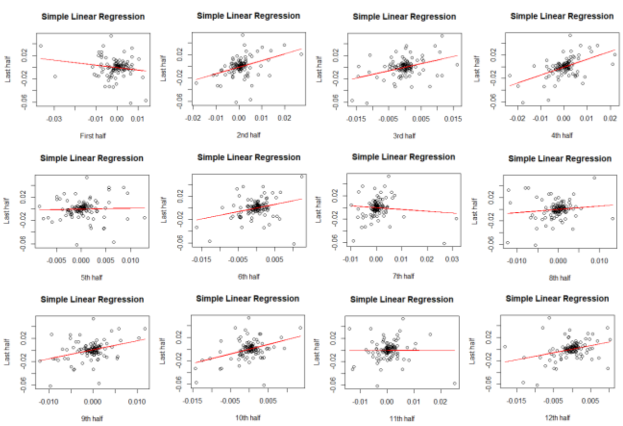
Fig. 5. Regression figures of all the half hours on the last half during COVID.

Through the analysis of the regression results, we find that the momentum effect in the whole sample period is not as significant as the intraday momentum effect at the minute level in the previous sample. We find that the momentum effect of the first half hour on the logarithmic returns of the last half hour reverses when β values are not significant. The emergence of this reversal effect is mainly related to the investor sentiment mentioned above and the volatility of the market. The flood of information and changes in investor sentiment after the closing bell are likely to affect yields in the first hour and a half of trading. Markets digest this information as they trade. Thus, investor optimism increases the strength of the reversal effect, but pessimism reduces it. Investor sentiment is influenced by market factors such as stock prices and non-market factors such as policies, and all kinds of information will have an effect on it. When stock prices rise or favorable policies are introduced, investors tend to show optimism and increase trading behavior. However, under the action of risk preference and loss aversion, investors tend to buy stocks with poor performance in the past to expand expected returns, and sell stocks with better performance at present to realize existing profits. Thus, more reversal effect is generated, which explains the reversal momentum effect generated in the first half hour.

Later, as institutions and investors continued to join in the trading behavior, the "herd effect" began to appear, especially in the context of COVID economic crisis, this phenomenon is more obvious. As the overall stock market is in a more pessimistic state, investors tend to have a cautious trading style, so the positive momentum effect continues to be reflected in the market during the subsequent trading hours.

VI. Conclusion

This paper considered that in the era when low-frequency trading data prevailed, the traditional time series analysis method would not be very accurate in estimating the embedded volatility with the parameter method due to the lack of information contained in the sample. Therefore, we need to adopt a nonparametric, not influenced by different time range and robust method to estimate volatility, based on the second-level of high-frequency data to achieve more accurate depiction of volatility, thereby obtained the actual volatility measurement, to help investors better understand the nature of market noise, and achieve more accurate research and modeling of stock price volatility, so as to achieve the purpose of timing the market. Next, we paid more attention to the intraday momentum effect at the minute level, and used the historical price data of SPDR Dow Jones Industrial Average ETF Trust (DIA) to verify the intraday momentum effect of all half hours in a trading day on the last half hour in the full sample. It is pointed out that the intraday momentum effect will be more obvious in the economic crisis caused by financial system factors similar to the 2008 financial crisis. In severe public event crises like COVID-19, the intraday momentum effect may turn due to the digestion of market information and the influence of investor sentiment, but it will still maintain the normal positive momentum effect for part of the time.

In future studies, researchers may introduce more analytical data, such as trade interval and trading volume, to study the relationship between market volatility modeling and intraday momentum effect in the era of more available high-frequency trading data and more advanced computer computing power. At the same time, with the progress of computer algorithm technology, researchers can also combine machine learning and deep learning algorithms to study whether completely nonparametric models can be better than econometric methods in predicting realized volatility [25]. Zhang, *et al*. 's research [26] indicates that the prediction performance of the model can be significantly improved by using the commonality of intraday fluctuation, that is, the adjusted r-squared value in the linear regression of the realized volatility of a given stock relative to the realized volatility of the market. Similar results give researchers new perspectives on the subject. There is no doubt that the historical performance of stocks reflected by volatility and stock historical data will continue to be the focus of the future timing the market, and will have an important impact on portfolio management, asset price evaluation, financial derivatives pricing and financial risk management. Therefore, whether the conclusions obtained in this paper can be maintained under the influence of a wider range of investor sentiment and the mechanism of the influence of investor sentiment on stock price fluctuations still need further verification by researchers.

Conflict of Interest

The author declares no conflict of interest.

Author Contributions

Chenyang Yu conducted the independent research.

Acknowledgment

Chenyang Yu thanks for the guidance under Dr. Erik S. Yan in UCLA for the conducting of this paper.

References

[1] S. Yan, “Estimating stochastic volatility within a trading day,” Unpublished doctoral dissertation, UCLA, Los Angeles, CA, 2017.

[2] L. Gao, Y. Han, S. Z. Li, and G. Zhou, “Market intraday momentum,” *Journal of Financial Economics*, vol. 129, issue 2, pp. 394-414, 2018.

[3] N. Jegadeesh and S. Titman, “Returns to buying winners and selling losers: Implications for stock market efficiency,” *Journal of Finance*, vol. 48, pp. 65–91, 1993.

[4] H. Shefrin and M. Statman, “The disposition to sell winners too early and ride losers too long: Theory and evidence,” *Journal of Finance*, vol. 40, pp. 777–790, 1985.

[5] T. Odean, “Are investors reluctant to realize their losses?” *Journal of Finance*, vol. 53, pp. 1775–1798, 1998.

[6] P. R. Locke and S. C. Mann, “Do professional traders exhibit loss realization aversion?” Working paper, Texas Christian University, 2000.

[7] J. D. Coval and T. Shumway, “Do behavioral biases affect prices?” *Journal of Finance*, vol. 60, pp. 1–34, 2005.

[8] M. S. Haigh and J. A. List, “Do professional traders exhibit myopic loss aversion? An experimental analysis,” *Journal of Finance*, vol. 60, pp. 523–534, 2005.

[9] A. P. Pfleiderer, “A theory of intraday patterns: Volume and price variability,” *Review of Financial Studies*, vol. 1, no. 1, pp. 3-40, 1988.

[10] M. Hora, “Tactical liquidity trading and intraday volume,” Working paper, Credit Suisse, 2006.

[11] A. Kirilenko, A. S. Kyle, M. Samadi, and T. Tuzun, “The flash crash: High-frequency trading in an electronic market,” *The Journal of Finance*, vol. 72, no. 3, pp. 967-998, 2017.

[12] T. G. Andersen and T. Bollerslev, “Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies,” *Journal of Finance*, vol. 53, no. 1, pp. 219–265, 1998.

[13] T. G. Andersen and T. Bollerslev, “Answering the skeptics: Yes, standard volatility models do provide accurate forecasts,” *International Economic Review*, vol. 39, pp. 885-905, 1998.

[14] T. G. Anderson, T. Bollerslev, F. Diebold, and P. Labys, “Modeling and forecasting realized volatility,” *Econometrica*, vol. 71, no. 2, pp. 579–625, 2003.

[15] R. C. Merton, “On estimating the expected return on the market: an exploratory investigation,” *Journal of Financial Economics*, vol. 8, no. 4, pp. 323–361, 1980.

[16] O. Barndorff-Nielsen and N. Shephard, “Variation, jumps and high frequency data in financial econometrics,” in *Proc. Ninth World Congress Advances in Economics and Econometrics, Theory and Applications*, 2007, pp. 328-372.

[17] K. Christensen, R. C. Oomen, and M. Podolskij, “Fact or friction: Jumps at ultra-high frequency,” *Journal of Financial Economics*, vol. 114, no. 3, pp. 576-599, 2014.

[18] K. Christensen, U. Hounyo, and M. Podolskij, “Is the diurnal pattern sufficient to explain the intraday variation in volatility? A nonparametric assessment,” CREATES Research Working Paper, 2017.

[19] B. Ellickson, M. Sun, D. Whang, and S. Yan. (2018). Estimating a local Heston model. SSRN Archive. [Online]. Available: https://ssrn.com/abstract=3108822

[20] S. Yan, “Estimating stochastic volatility within a trading day,” Doctoral dissertation, UCLA, Los Angeles, CA, 2017.

[21] O. Barndorff-Nielsen and N. Shephard, “Power and bipower variation with stochastic volatility and jumps,” *Journal of Financial Econometrics*, vol. 2, no. 1, pp. 1–37, 2004.

[22] H. Jiang, W. Wu, and S. Wei, “The impact of COVID-19 on global stock market risk: A cross-market test based on ESA method,” *International Financial Studies*, no. 3, p. 11, 2021.

[23] M. A. Lasfer, A. Melnik, and D. C. Thomas, "Short-term reaction of stock markets in stressful circumstances," *Journal of Banking & Finance*, vol. 27, no. 10, pp. 1959-1977, 2003.
[24] R. D. Smith, "Responding to global infectious disease outbreaks: Lessons from SARS on the role of risk perception, communication and management," *Social Science & Medicine*, vol. 63, no. 12, pp. 3113-3123, 2006.
[25] A. Bucci, "Realized volatility forecasting with neural networks," MPRA Paper, 2019.
[26] C. Zhang, Y. Zhang, M. Cucuringu *et al.* (2022). Volatility forecasting with machine learning and intraday commonality. arXiv e-prints. [Online]. Available: https://arxiv.org/abs/2202.08962