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Study of Pandemic, Investor Sentiment, and Stock Returns with Machine Learning

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***Abstract*— *After the first COVID-19 patient was diagnosed in China, in December 2019, the market's reaction to the pandemic evolved from initial unawareness and minimal response to rapid panic among investors as the outbreak escalated. As the pandemic continued to develop, the market gradually absorbed the impact, and stock market performance experienced a process of decline from high to low points. From the perspective of behavioral finance, the development of the pandemic suppressed the stock market through both profitability and risk preferences. The initial lack of understanding of the situation further exacerbated market volatility. This paper examines the correlation between the development of the pandemic and daily stock returns from March to June 2020, as well as the mechanism through which the pandemic affected investor sentiment. It reveals a negative correlation between the growth rate of infections and daily stock returns, and how the pandemic increased investors' pessimism, influencing their trading behavior by increasing turnover rates, thereby exacerbating the negative impact on stock returns. By empirically revisiting the impact of the 2020 COVID-19 pandemic on stock market investor behavior, this study provides insights for predicting and responding to the impact of the 2019 novel coronavirus (2019-nCoV) on the stock market.*

***Keywords*— Pandemic, Investor Sentiment, Stock Returns**

I. INTRODUCTION

Behavioral finance theory suggests that investor sentiment influences trading behavior. The occurrence of black swan events, such as pandemics, undoubtedly increases investors' pessimism[1]. Due to risk aversion, investors tend to lower their valuation of stocks and reduce their willingness to trade, further exacerbating the decline in stock returns[2]. This paper studies the impact of the COVID-19 pandemic on stock market returns during the 2020 outbreak and further analyzes how the growth rate of infections increased investors' pessimism, influencing their trading behavior and thereby exacerbating the negative impact on stock returns[3-4]. The structure of this paper is as follows: Section 2 reviews the literature and proposes research hypotheses; Section 3 introduces the research design; Section 4 presents empirical research and analyzes the results; Section 5 conducts robustness tests; and Section 6 concludes.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature Review

2.1.1 Black Swan Events

Nassim Taleb first introduced the term "black swan" in 2001, defining it as an event that satisfies the following three characteristics:

1. **Unexpectedness**: The event is unpredictable based on historical experience and occurs suddenly.
2. **Extreme Impact**: The event has a significant impact, either positive or negative.
3. **Retrospective Predictability**: Although the event is sudden, upon review, signs of its occurrence can be identified, making it seem explainable and predictable.

In recent years, a series of black swan events in China have caused significant shocks to related industries and brought unpredictable risks to the financial market[5-8]. Events such as the melamine-tainted milk powder, Shuanghui's lean meat powder, Changsheng Bio-technology's vaccine fraud[9-11], Everbright Securities' fat-finger error, and Jiugui Liquor's plasticizer exceeding the standard have caused catastrophic impacts on related industries, leading to sharp declines in stock prices[12-14]. The panic and herd behavior among investors further exacerbated the impact of these events.

Deng et al. (2014) pointed out that China's stock market is relatively young, with an imperfect system and structural defects[13-16]. The low level of financial market regulation and the quality of practitioners, along with the limited variety of financial products, make the Chinese market more susceptible to the impact of black swan events, leading to devastating consequences for individual stocks and the entire financial market[17-19]. Zhou and Zhao (2013) studied the impact of the 2012 "toxic capsule event" on the stock returns of A-share pharmaceutical companies, proving that the impact of this black swan event was significant but had a certain lag. Different stocks within the same industry category showed varying positive and negative effects, volatility, and sensitivity to the impact[20].

The outbreak of the 2020 COVID-19 pandemic, as a sudden global infectious disease and public health event, was unexpected and had an extreme impact on China's macroeconomy and social life, including the catering, tourism, film, transportation, and education industries. The initial lack of timely information disclosure by local governments to avoid public panic, coupled with underdeveloped communication methods and misjudgments about the pandemic's development, contributed to the failure to control the spread of the virus in time[21-23]. Therefore, the COVID-19 event satisfies the three conditions of a black swan event, but empirical research on its impact on China's stock market and investor sentiment remains limited.

2.1.2 Investor Sentiment and Stock Returns

Currently, the proportion of institutional investors in China's stock market is relatively low compared to developed capital markets, with individual investors dominating[24]. Therefore, trading behavior is more susceptible to the influence of individual investor sentiment. An increasing number of scholars are studying how to construct investor sentiment indices, the characteristics of sentiment effects, and their mechanisms[25].

Baker and Wurgler (2007) proposed using retail investor trading, mutual fund flows, trading volume, dividend premium, closed-end fund discounts, option implied volatility, IPO first-day returns, and the number of IPOs as proxy variables for investor sentiment[26-19]. Zhang and Yang (2008) used unexpected investor account growth rates as an investor sentiment index to analyze the relationship between investor sentiment fluctuations and characteristic portfolio returns, proving that investor sentiment fluctuations are an important factor affecting stock returns[30-32]. Yin and Wu (2019) extracted high-frequency sentiment data from real-time posts on the Shanghai Stock Exchange and stock bar using data mining techniques and constructed an intraday high-frequency investor sentiment index using semantic analysis[33-36]. They found that intraday investor sentiment in the Chinese stock market can positively predict market performance, and in extreme market environments such as surges or crashes, the impact of sentiment on intraday returns is more significant than lagged returns[37-39]. Noise trading is an important driving force behind the impact of investor sentiment on stock returns. Liu and Wang (2015) empirically studied the changes in returns of different types of stocks during different sentiment periods by dividing stocks based on investor sentiment indices and stock characteristics, proving that investor sentiment plays an important role in stock pricing in China[40]. Yin (2018) used principal component analysis to construct an investor sentiment index and added it as a sentiment factor to the Fama-French three-factor model[41]. The study found that investor sentiment significantly affects stock returns, but its explanatory power is limited. The three-factor model with the sentiment factor added can better explain stock returns.

2.2 Theoretical Analysis and Hypothesis Development

Based on the existing literature, this section theoretically analyzes the impact of pandemic development on investor sentiment and stock returns and proposes relevant research hypotheses[42].

According to Fama's Efficient Market Hypothesis (EMH) proposed in 1970, stock prices fully reflect all available information about the asset, i.e., "information efficiency." When information changes, stock prices will inevitably change accordingly. When a pandemic occurs, its impact on the stock market is directly reflected in stock prices, trading volume, price changes, and returns, causing stock price fluctuations, mostly in the form of sustained declines. The main reason for this sustained impact is the efficiency of information transmission, investor reaction, and decision-making time. Investors may underreact due to reliance on experience and asymmetric information, or overreact due to market panic. Based on this analysis, this study proposes the following hypothesis regarding the impact of the pandemic on stock returns:

H1: The growth rate of infections is negatively correlated with daily stock returns. The faster the pandemic develops, the lower the returns of the Shanghai Composite Index.

The pandemic may affect stock returns through two mechanisms: first, the outbreak of the pandemic directly impacts stock returns by affecting the macroeconomy and industries such as catering, tourism, film, transportation, and education. Second, the pandemic increases investors' pessimism, further exacerbating the impact on stock prices. When negative news about the pandemic is released, the market reacts with bearish news, leading to massive stock sell-offs and sharp declines in stock prices. Investors exhibit herd behavior and risk aversion, following the trend to sell, and the contagion effect of investor sentiment exacerbates the extreme impact. Based on this analysis, this study proposes the following hypotheses regarding the impact of the pandemic on stock returns and investor sentiment:

H2a: The faster the growth rate of infections, the higher the investors' pessimism, and the higher the stock turnover rate.

H2b: The faster the growth rate of infections, the lower the investors' willingness to participate in stock trading, and the lower the stock liquidity.

III. SAMPLE AND DATA DESCRIPTION

3.1 Sample Selection and Data Sources

This study selects samples from the daily data of global COVID-19 infections published by the World Health Organization (WHO) in 2020 (most of the confirmed cases were in mainland China) and daily data on the Shanghai Composite Index market conditions and market capitalization provided by the Wind database.

The study period is from March 25, 2020, to June 15, 2020, covering stock trading days during the COVID-19 outbreak. The development of the 2020 COVID-19 pandemic can be divided into the following four stages:

1. **Outbreak Period**: On December 5, 2002, the first COVID-19 patient was identified in Guangdong, China. To avoid public panic, local governments did not release relevant information, so the stock market was not significantly affected.
2. **Fermentation Period**: On February 11, 2020, the Guangdong provincial government officially announced the COVID-19 outbreak, which was classified as a local epidemic. The then Minister of Health publicly stated that COVID-19 in China was under control. Due to underdeveloped communication methods at the time, large-scale events such as the China-Brazil football match and the GLOBAL Spring Marathon continued as usual, exacerbating the spread of the virus. During this period, the market surged, with the Shanghai Composite Index rising by 23.6%.
3. **Explosion Period**: On April 17, 2020, the Standing Committee of the Political Bureau of the CPC Central Committee held a meeting, and the

then Minister of Health and the Mayor of Beijing were dismissed, marking a turning point in the COVID-19 event. The incidence rate in key areas increased, the May Day holiday was canceled, and isolation control measures were implemented in key areas. The COVID-19 outbreak drew market attention and panic, and the severity of the pandemic was recognized. The Shanghai Composite Index fell by 7.5% over two weeks.

4. **Ending Period**: After May 2020, the pandemic was effectively controlled. The market stabilized in mid-to-late May, and confidence was restored. Market performance fluctuated until the COVID-19 pandemic basically ended by the end of June.

On March 15, 2020, the World Health Organization (WHO) officially named the disease COVID-19, and from March 25 onwards, the statistics included confirmed cases in mainland China. The global infection statistics published by the WHO show that the number of confirmed cases gradually stopped increasing by mid-June. Table 1 presents the descriptive statistics of the main variables in this study.

Table 1: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Median**
Daily Stock Return	0.001	0.064	-0.030	0.034	0.000
Pandemic Growth Rate	0.063	0.951	0.000	0.951	0.018
Turnover Rate (%)	1.600	3.471	0.500	3.971	1.409
Liquidity	46045364.555	676633628.705	4561958.795	681195587.500	17772314.440
Momentum Factor	0.001	0.064	-0.030	0.034	0.000
Market Capitalization (10,000 yuan)	8062.055	953.000	7606.000	8559.000	8070.000
Market-to-Book Ratio Factor	0.001	0.025	-0.009	0.016	0.000

3.2 Variable Definitions and Descriptions

3.2.1 Dependent Variables

1. **Daily Stock Return**: Calculated using the daily data of the Shanghai Composite Index market conditions from the Wind database, is the closing price on the previous day. The Shanghai Composite Index includes all stocks listed on the Shanghai Stock Exchange, with newly listed stocks included in the index calculation from the second day of listing. This index reflects the price changes of stocks listed on the Shanghai Stock Exchange. Mehra and Sah (2020) found that fluctuations in investors' subjective preferences, especially regarding risk and discount factors, can potentially affect stock price volatility.
2. **Investor Sentiment**: Mainly characterized by the stock turnover rate and liquidity. The daily turnover rate data from the Shanghai Stock Exchange's global macroeconomic database in the Wind database is used. Li et al. (2015) proposed using the turnover rate to indirectly measure the difficult to measure directly measure indicator of investor disagreement. Liquidity is calculated using the formula Stock Daily Trading Volume/ Stock Daily Return Percentage Stock Daily Trading Volume/ Stock Daily Return Percentage (Amihud, 2002; Liang et al., 2008). A higher liquidity index value indicates that more trading volume is required for a unit change in stock price, meaning higher liquidity.

3.2.2 Main Explanatory Variable

This study uses the development of the pandemic as the explanatory variable, using the daily global infection data published by the World Health Organization. The growth rate of daily infections is calculated using the formulaand the logarithm of this result is taken to calculate the daily growth rate of infections.

3.2.3 Main Control Variables

1. **Market Capitalization**: The logarithm of the daily market capitalization of the Shanghai Composite Index. Hong et al. (2006) found that market capitalization is negatively correlated with stock turnover rate and positively correlated with the degree of disagreement, as greater disagreement can generate more speculative trading. Merton (1987) argued that stocks with higher market capitalization have higher turnover rates, as companies with higher market

capitalization may have more investors and more active trading behavior.

2. **Market-to-Book Ratio Factor**: In the Fama-French three-factor model, Fama proposed that market risk premium, size, and market-to-book ratio factors can be used to explain stock excess returns. Su and Mai (2004) analyzed the theoretical and empirical relationship between liquidity and asset pricing in China's stock market, proposing that China's stock market has a significant liquidity premium. Assets with low turnover rates, high trading costs, and low liquidity have higher expected returns. The reason for the liquidity premium is trading costs rather than trading frequency. Similar to foreign markets, value stocks have higher returns than growth stocks. Therefore, liquidity, size, and value effects are important factors in asset pricing in China's stock market. Zhang et al. (2006) studied the negative correlation between stock turnover rates and cross-sectional stock returns in China's stock market, proving that turnover rates can be used as a proxy for the volatility of investor heterogeneous beliefs. There is a certain positive correlation between stock turnover rates and market-to-book ratios. Under the conditions of market safety constraints and the simultaneous existence of investor heterogeneous beliefs, speculative trading may lead to stock price overvaluation and speculative bubbles, which can be measured by the market-to-book ratio.
3. **Momentum Factor**: In addition to the Fama-French three factors, the momentum factor is also an important factor in explaining stock returns. Following Chen et al. (2018), the momentum factor is calculated using the higher-order criterion of daily stock returns. Chen et al. (2014) studied the relationship between two "relative price momentum" portfolios and traditional momentum based on the anchoring effect and disposition effect in behavioral finance, finding that the anchoring effect and disposition effect are important reasons for the momentum effect in China's stock market. Gao et al. (2014) re-examined the momentum effect in China's A-share market using stock return data from 1994 to 2011, finding that stable momentum returns exist when the formation period is 2-4 weeks and the holding period is 1-3 weeks. Factors such as size, market-to-book ratio, and industry can explain about 50% of momentum returns. Existing behavioral finance theories cannot explain the significant differences in momentum effects among stocks of different sizes, market-to-book ratios, and turnover rates. The momentum effect has different formation mechanisms in winner and loser portfolios.

Table 2: Variable Names and Definitions

Variable Symbol	**Variable Name**	**Variable Definition**
Turnover	Daily Stock Turnover Rate	Daily Trading Volume / Current Circulating A Shares
Liquidity	Daily Stock Liquidity	Daily Trading Volume / Daily Stock Return Percentage
Momentum	Momentum Factor	Lagged term of returns
InValue	Market Capitalization	Logarithm of the total market value of circulating shares at a specific time
HML	Market-to-Book Ratio	Shareholder Equity / Company Market

IV. EMPIRICAL RESULTS AND ANALYSIS

4.1 Impact of Pandemic Development on Stock Returns

4.1.1 OLS Regression Analysis of the Impact of Pandemic Development on Stock Returns

This study uses the following OLS regression model to examine the relationship between the growth rate of infections and the daily returns of the Shanghai Composite Index:

is the residual term. Control variables include the momentum factor, market capitalization, and market-to-book ratio. The regression results are shown in Table 3.

Table 3: Regression Results of the Impact of Infection Growth Rate on Daily Stock Returns

Variable	**Return**
InCOVID-19	-0.277**
	(0.117)

Momentum	0.147
	(0.161)
InValue	4.061E-005***
	(0.000)
HML	1.546***
	(0.339)
Intercept	0.328***
	(0.117)
Observations	55
Adjusted R-squared	0.503

Note: Figures in parentheses are robust standard errors. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

The results show that the growth rate of infections is negatively correlated with the returns of the Shanghai Composite Index. A 1% increase in the growth rate of infections leads to a 0.277% decrease in the returns of the Shanghai Composite Index, i.e., returns decrease during the outbreak period, supporting hypothesis H1.

4.1.2 VAR Analysis of the Impact of Pandemic Development on Stock Returns

1. **VAR Model**

In the VAR model, each time series is modeled as depending on its own lagged values and the lagged values of all other variables

2. **ADF Test**

Before constructing the VAR model, an ADF test is conducted on the input variables, daily stock returns, and the growth rate of infections. The test results are as follows:

Table 4: ADF Test Results of Original Data

	Test Statistic	1% Value	Critical Value	5% Value	Critical Value	10% Value	Critical Value
Daily Return	-7.234	-3.574	-2.927	-2.598	0.000		
In COVID-19	-2.029	-3.574	-2.927	-2.598	0.274		

The ADF test results show that the daily stock return indicator is stationary, while the infection growth rate indicator is non-stationary and requires differencing to pass the stationarity test before constructing the VAR model.

Table 5: ADF Test Results After First-Order Differencing

	Test Statistic	1% Value	Critical Value	5% Value	Critical Value	10% Value	Critical Value
Daily Return	-7.234	-3.574	-2.927	-2.598	0.000		
In COVID-19	-10.219	-3.576	-2.928	-2.599	0.000		

The results show that both indicators are stationary. Based on the LR, FPE, AIC, HQIC, and SBIC criteria, the optimal lag order is 1, as all criteria except SBIC are minimized at this lag order. Therefore, a VAR model with a lag order of 1 is constructed.

Table 6: Information Criterion Calculation Results

Lag	LL	LR	df	P	FPE	AIC	HQIC	SBIC
0	-23.8084				.010529	1.1221	1.15189	1.20161*
1	-18.2796	11.058*	4	0.026	.009855*	1.05563*	1.14498*	1.29415
2	-15.336	5.8871	4	0.208	.010332	1.10157	1.25048	1.4991
3	-11.2046	8.2628	4	0.082	.010305	1.09585	1.30434	1.6524
4	-6.51057	9.3881	4	0.052	.010053	1.06568	1.33373	1.78123
5	-4.21702	4.5871	4	0.332	.010922	1.13987	1.46749	2.01444
6	-2.78764	2.8587	4	0.582	.01237	1.25164	1.63882	2.28522
7	.881646	7.3386	4	0.119	.012774	1.26602	1.71277	2.45861
8	4.23472	6.7062	4	0.152	.013456	1.29414	1.80046	2.64575

3. **Granger Causality Test**

Granger (1969) proposed the concept of causality. If a bivariate sequence.

The Granger causality test results for the VAR(1) model are as follows:

Table 7: Granger Causality Test Results

	Excluded	F	df	df_r	p-value
Daily Return	In COVID-19	3.191	1	50	0.080
Daily Return	ALL	3.191	1	50	0.080
In COVID-19	Daily Return	1.022	1	50	0.317
In COVID-19	ALL	1.022	1	50	0.317

The table shows that the growth rate of infections has a significant impact on daily stock returns. The null hypothesis is rejected at the 10% significance level, indicating that the development of the pandemic significantly affects stock returns.

4. **Impulse Response Analysis**

The figure below shows that when a negative shock is applied to the growth rate of infections in the current period, daily returns reach their minimum in the first period, showing a clear downward trend[43]. However, they rise in the second period and then slowly decline, gradually approaching 0 by the fourth period. Therefore, the development speed of the pandemic has a significant impact on stock returns in the short term, but this impact disappears within about four periods.

4.2 Impact of Pandemic Development on Investor Sentiment

4.2.1 Impact of Pandemic Development on Turnover Rate

Chen et al. (2018) proposed that air quality affects stock returns through two mechanisms: first, poor air quality increases investors' pessimism, increasing turnover rates and thereby reducing portfolio returns; second, when air quality is poor, investors' willingness to trade decreases, and reduced liquidity also leads to lower portfolio returns. This study proposes a similar hypothesis: the development of the pandemic will also affect the returns of the Shanghai Composite Index through two different mechanisms. An OLS regression model is used to examine the relationship between turnover rates and the growth rate of infections is the residual term. Control variables include the momentum factor, market capitalization, and market-to-book ratio.

From Table 4, the coefficient of the growth rate of infections is significantly positive at the 5% level. A 1% increase in the growth rate of infections leads to a 23.154% increase in stock turnover rates. The regression results support hypothesis H2a, indicating that the more severe the pandemic, the higher the investors' pessimism, the lower the valuation and expectations for stocks, and the higher the risk aversion, leading investors to be unwilling to hold stocks. This increases disagreement among investors, thereby increasing turnover rates and trading volume. During the outbreak period, key areas such as Beijing and GLOBAL, with their large populations and high investor numbers, experienced strong pessimism, leading to lower stock valuations and higher turnover rates.

Table 8: Regression Results of the Impact of Infection Growth Rate on Turnover Rate

Variable	Return
InCOVID-19	23.154***
	(5.654)
Momentum	16.941**
	(7.293)
InValue	0.002***
	(0.001)
Intercept	-16.708***
	(0.001)
Observations	55
Adjusted R-squared	0.455

Note: Figures in parentheses are robust standard errors. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

4.2.2 Impact of Pandemic Development on Liquidity

This study follows Chen et al. (2018) and Liang et al. (2008) in using the Amihud measure to assess liquidity and uses the following regression model to examine the relationship between the growth rate of infections and liquidity[44-46]: the residual term. Control variables include the momentum factor, market capitalization, and market-to-book ratio. The regression results show that the coefficient of the growth rate of infections is not significant, and the adjusted R-squared is low, indicating limited explanatory power. Therefore, hypothesis H2b is not supported.

Table 9: Regression Results of the Impact of Infection Growth Rate on Liquidity

Variable	**Return**
COVID-19	-1.891E7
	(1.081E8)
Momentum	-1.009E9
	(1.130E9)
Value	5.297E4
	(7.575E4)
HML	-2.891E9
	(2.560E9)
Intercept	3.750E8
	(6.150E8)
Observations	55
Adjusted R-squared	0.076

Note: Figures in parentheses are robust standard errors. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

V. CONCLUSIONS

This paper concludes that the growth rate of COVID-19 infections is negatively correlated with daily stock returns. The more severe the pandemic, the lower the returns of the Shanghai Composite Index. The pandemic may affect stock returns through two mechanisms: first, by impacting the macroeconomy and industries such as catering, tourism, film, transportation, and education, directly affecting stock returns; second, by increasing investors' pessimism. When investors receive negative news about the pandemic, they tend to sell off stocks due to risk aversion and herd behavior, leading to sharp declines in stock prices. The contagion effect of investor sentiment exacerbates the extreme impact. This paper focuses on the second mechanism, the impact of investor sentiment on stock returns, which operates through two pathways: first, as the growth rate of infections increases, investors' pessimism increases, leading to higher turnover rates and lower returns; second, the increase in the growth rate of infections reduces investors' willingness to participate in stock trading, leading to lower liquidity and lower returns.

This paper validates the above hypotheses through a series of empirical studies. First, using the daily closing prices of the Shanghai Composite Index to calculate daily stock returns and the daily global infection data published by the World Health Organization to calculate the daily growth rate of infections, the results show that the growth rate of infections is negatively correlated with the returns of the Shanghai Composite Index. A 1% increase in the growth rate of infections leads to a 0.277% decrease in the returns of the Shanghai Composite Index. Then, using the turnover rate as an indirect measure of investor disagreement and calculating liquidity as the daily trading volume divided by the absolute value of the daily stock return percentage to measure the trading volume required for a unit change in stock price, the results show that the impact of the pandemic on investor sentiment is through increasing turnover rates rather than reducing liquidity and willingness to trade, further exacerbating the impact on returns. A 1% increase in the growth rate of infections leads to a 23.154% increase in stock turnover rates.

Under the impact of the pandemic, the stock market continues to fluctuate, with short-term stock prices dominated by investor sentiment and subject to negative shocks. However, as the pandemic is basically alleviated and controlled, market confidence will gradually restore. Compared to the 2020 COVID-19 outbreak, the 2019 novel coronavirus (2019-nCoV) outbreak spread more quickly, but the national response has been more proactive. The impact on various industries in terms of time and extent is limited, and market panic will be quickly repaired. It is necessary to focus on turning point trends and the market conditions of various sectors.

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