COVID-19 and China's Foreign Direct Investment Inflow- Stress Tests Based on Extreme Gradient Boosting Model and Policy Implications

Xinhui Zhou [1], Yuzhe Li [2] *, Weidong Zhao [1], Yun Zhang[1], Ziyu Yan[3]

[1] Shanghai Lixin University of Accounting and Finance, Shanghai, China

[2] City University of Hong Kong, Hong Kong, China

[3] New York University, New York, America

* Corresponding Author Email: davy1@126.com

Abstract. Foreign direct investment (FDI) is essential to world economic growth, global industrial chain optimization, technology diffusion, and product innovation. This study identifies several macro-level factors affecting FDI inflow to China after discussing possible mechanisms through which COVID-19 influences FDI. Then, it tests three different stressful scenarios simulating the COVID-19 influence on China's FDI inflow with a regression model estimated by extreme gradient boosting (XGBoost) in Python. Results show that the rampant COVID-19 pandemic and increasing global investment risks would have a substantial and negative impact not only on global FDI size, investment rules, and investment structure, but also on FDI inflow to China. Without effective measures being taken, from January 2020 to March 2022, losses in China's annual FDI inflow could reach 5.71 percent to 11.28 percent, but the country's actual annual FDI inflow is much higher. The extraordinary measures adopted by the Chinese government include preventing pandemic measures that are prompt and effective as well as targeted macroeconomic regulation policies. They make a rapid recovery or even improvement in China's economic fundamentals, which in turn enhance China's attractiveness to FDI and the FDI size, more than offsetting the negative effect of COVID-19 on FDI inflow to China. Finally, this paper proposes several countermeasures in macro-economic regulation and industrial policy adjustment to prevent and mitigate the negative influence of COVID-19 on FDI.

Keywords: COVID-19 pandemic, Foreign direct investment, Stress test, Extreme gradient boosting model.

1. Introduction

Globally, foreign direct investment (FDI) is essential to world economic growth, global industrial chain optimization, technology diffusion, and product innovations [1]. Since adopting the reform and opening-up policies, China has been active in creating favorable conditions to maximize FDI's effects, including raising tax revenue, creating employment, enhancing trade, stimulating business innovations, and driving industrial upgrading, all of which are conducive to China's rapid economic growth [2]. However, in recent years, multiple unfavorable developments such as sluggish worldwide economic growth, the trend of reversing globalization in international trade, increasing trade frictions, and rising geopolitical tensions result in smaller FDI size and lower FDI returns [3-4]. The COVID-19 pandemic, since its outbreak in December 2019, has exacerbated a huge influence on global FDI and interrupted the global supply chain substantially [5-6]. Under the uncertainty of circumstance [7], FDI inflow to China may also fluctuate substantially as multinational companies would be more cautious about their global investments [8-9], leading to a considerable impact on the Chinese economy, so the government should increase the public investment to improve the investment environment [10]. While the current studies do not research and measure the COVID-19 influence on FDI inflow to China under stress circumstance. Therefore, coupled with a literature review, this paper identifies several characteristics of the pandemic and the mechanisms through which the pandemic could affect the FDI inflow to China and operates a stress test by XGBoost model on some simulated scenarios to quantify the specific effect of COVID-19 on FDI inflow to China. The results are discussed through comparative analyses.

FDI accounts for a large share of international capital movements. It is instrumental in enhancing the efficiency of capital allocation, promoting host countries' trade, employment, and economic growth, as well as improving their status in the global value chain. Prior works have found numerous factors affecting FDI. Moore (1993) analyzes FDI inflow to German's manufacturing sector during 1980–1988 with a fixed-effects model and confirms that host countries' market size and labor cost have significant effects on FDI inflow [11]. Hu (2006) employs a time series model to verify that potential market size and government's relevant investment incentive policies affect FDI inflow, while tax concessions' effects are less significant [2]. White and Fan (2006) find that FDI is affected not only by the industries and the internal factors of specific companies to be invested but also by the changes in host country political and economic environment and global risks [3].

Major global events, such as economic and financial crises, are important factors affecting FDI. Sun and Wang (2009) find that the global financial crisis makes multinational corporations more cautious about their investments in the manufacturing sector [8]. In contrast, investments in life science, healthy food, and information and communication industries are less affected by the crisis. Ucal et al. (2010) use a semiparametric Generalized Partial Linear Model for panel data of 148 developing economies during 1995–2007 [9]. The results suggest that FDI decrease after the financial crisis of 2008 can be mainly explained by multinational corporations' reluctance to expand and their lower capabilities to invest abroad. Jin, Jian, and Chen (2010) examine the monthly data related to FDI inflow to China during 1998–2008 and find that the financial crisis could affect the FDI inflow to China through its effects on developed countries' stock market liquidity, interest rates, stock market trading volume, and commodity export [12]. Giroud and Ivarsson (2020) observe FDI flow for major countries [5]. They find heterogeneous effects of global crises on developed and developing countries. FDI inflow to developing countries is relatively stable. However, during the subprime crisis in 2008, FDI inflow declined notably while FDI outflow rose with minor fluctuations. Moreover, during the H1N1 pandemic in 2009, FDI inflow to Mexico and surrounding countries was affected.

COVID-19 has become an important factor affecting the global economy and could have a significant impact on FDI. Zhang and Liao (2020) argue that COVID-19 has had a significant impact on the investment rules, modes, structure, and returns of FDI globally [13]. Zhan (2020) suggests that the long-term impact of COVID-19 on a country FDI flow may be reflected in the policy orientation of the country [14]. Many countries have established specialized investment and development institutions to facilitate investment and support global investors. Alkahtani et al. (2021) indicate that the global supply chain crisis caused by the COVID-19 pandemic could affect production and supply chain negatively, which in turn affects global FDI [6]. Many have examined the determinants of FDI inflow to China. Hu (2021) believes that there are considerable uncertainties over the FDI inflow to China given the sluggish economic growth in major economies and the difficulties in containing the COVID-19 pandemic [7]. Although there is considerable room for China to increase FDI inflow in the short run, it will decline in the long run.

Some summarize the determinants of FDI. They include macro-level factors such as political landscape, economic policies, market size, as well as industry characteristics, and micro-level factors such as corporate strategy, labor costs, and investment willingness [15-16]. Among them, the global crisis has become an important determinant of global FDI. Considering the substantial uncertainties and heterogeneity of the impact for different countries and regions, we could argue that the internal mechanism of action is rather complex. Most of the studies on the COVID-19 influence on FDI focus on analyzing the effects and proposing targeted policies and measures. However, the results of the studies are quite mixed. Due to the short time frame and incomplete data, few studies have explored how COVID-19 affects FDI and then measured the effects quantitatively. With a theoretical analysis of the effects of COVID-19 on FDI, this paper summarizes possible mechanisms through which COVID-19 affects the FDI inflow to China. The data collected based on the analysis are placed into a Python-powered machine integrated learning system, which is used to estimate an extreme gradient boosting (XGBoost) model. A stress test is carried out with the model for different scenarios simulating the COVID-19 influence on the FDI inflow to China.

2. Mechanisms of COVID-19 Affecting Foreign Direct investment Inflow to China

2.1. Mechanisms for Negative Impact

The pandemic exacerbates the downside risk of the global economy, which implies lower return and heightened risk of FDI, causing the global FDI to shrink. The COVID-19 pandemic has increased the internal and external frictions in the international production system, stalling cross-border investment and trade growth, thereby hindering the development of the global economy. The downside risk of the global economy makes investors more cautious in their investment and producers reluctant in productive investment with a notably higher risk of the global FDI and accordingly lower investment return. Moreover, the global value chain is also disrupted. Given the widespread reach and extreme infectiousness of COVID-19, many countries have taken unprecedented measures to close their borders, such as banning entry and shutting off travel ties. Such border control measures notably hinder FDI projects. As FDI supply worldwide drops rapidly, the total FDI inflow to China also suffers a negative impact.

Also, the pandemic creates a hostile FDI policy environment, in which the changed investment rules cause a sharp decline in the global FDI total. COVID-19 has accelerated trade protectionism that has reversed globalization in recent years. Some countries are reviewing their industrial structures and opening up policies accordingly, speeding up the process of supply chain localization and diversification. Since the outbreak of COVID-19, some countries have adjusted bilateral and multilateral trade and investment rules as well as domestic and international investment policies of home and host countries. As a result, the policy environment for FDI investment has deteriorated notably, and investment rules have also been changed accordingly. In particular, some excessively restrictive regulatory policies have severely restricted global investment and development. As home countries tighten control of their multinational corporations, some of the corporations withdraw and shift their investments, leading to a sharp decline in the global FDI total. According to UNCTAD (United Nations Conference on Trade and Development) Global Investment Trend Monitor released on January 24, 2021, FDI in 2020 dropped by 42% year-on-year to USD 859 billion, a level not seen since the 1990s and over 30% lower than the investment trough immediately after the financial crisis in 2008.

The pandemic changes the pattern of global FDI investment activities and the structure of product demands, thereby affecting the investment structure of FDI. After the outbreak of the pandemic, many countries have taken strict measures to restrict movement. People’s socializing modes have evolved as a result. Remote working has been adopted by businesses where possible to reduce gatherings. These changes bring a huge impact on global FDI investment patterns. Due to the difficulties in FDI’s on-site due diligence and audit reviews, the share of local and near-shore investment activities is increasing, implying that the effectiveness and efficiency in pandemic control have become important determinants of a region’s competitiveness in attracting investment. The global industrial portfolio of FDI is also affected as the pandemic has opposite effects on different industries. The pandemic underlines the importance of digitization and health-related industries. Health care and biotechnology are the most valued industries for FDI under the pandemic. Cybersecurity is also a hot sub-sector that attracts a large amount of FDI. Offline catering, tourism, entertainment, retail, education, and other similar services are hit hard by the pandemic, suggesting that it is less likely that these industries could attract considerable FDI inflow.

2.2. Mechanisms for Positive Impact

China is attractive to FDI as it has successfully curbed the pandemic. Chinese governments at all levels invest heavily in controlling the pandemic, including engaging the public to fight the pandemic together. China has also rolled out a nationwide inoculation program that relies on the vaccines developed by itself. It is a model for other countries considering its success in curbing the pandemic's spread in China in a very timely manner. Such success is widely admired. Moreover, China has adopted a series of effective macro-level policies after the outbreak of COVID-19 to mitigate the pandemic's impact on China's economy. According to China's National Bureau of Statistics, China's GDP grew by 2.3 percent in 2020, making China become the only major economy in the world to buck the trend for growth in the year. The dual success in pandemic containment and economic development greatly enhances overseas direct investors' confidence and support and improves the attractiveness of China to global FDI.

The increased openness of China after the outbreak is conducive to enlarging the FDI inflow to China. The outbreak of COVID-19 does not waiver China's determination in enhancing open-up. With economic reforms targeting a new development pattern anchored on domestic circulation and supported by dual domestic-international circulation, China has taken larger steps in building a highly open economy, including a series of effective measures for enhancing economic connectivity with the outside world and facilitating foreign investment. These measures will contribute to the increase of FDI inflow to China. According to UNCTAD data released in January 2021, China became the world largest FDI destination in 2020, with annual FDI inflow rising by 4 percent to USD 163 billion.

3. Stress Test on COVID-19 influence on Foreign Direct investment Inflow to China

3.1. Selection of Variables

To study the impact of COVID-19 on FDI inflow to China, we examine monthly used FDI in China. A total of 234 monthly observations from October 2002 to March 2022 are used as the data set of a regression model.

According to prior studies, the influencing factors of FDI mainly include the global economic sentiment, the economic fundamentals of the host country, the relevant policies of the host country on FDI, and the presence of global risks. As the US stock market performance is a bellwether of the global economy and there is a potential mutual substitution relationship between the Chinese and US markets to some extent, it may affect the FDI inflow to China. Therefore, we choose the New York Stock Exchange Composite Index as an indicator of the global economic sentiment.

The economic fundamentals of the host country are reflected by four indicators. First, the economic growth rate of the host country is reflected by the year-on-year growth rate of China's GDP. A higher rate suggests that China performs well in economic development. Second, as China's 10-year bond yield moves in lockstep with GDP growth rate without notably idiosyncratic trends, the US 10-year treasury note rate is used instead. Higher treasury rates may imply that the market is bullish on the long-term economic performance of developed countries represented by America, and may curb FDI inflow to developing countries, such as China. Third, the equity of local companies acquired by foreign investors directly accounts for a large share of FDI. Therefore, the size and liquidity of stock markets will affect foreign investors' ability to liquidate their holdings. For this study, the tradable market capitalization of China's stock market to measure market activity is chosen. A more active market with larger capitalization is conducive to FDI inflow. Fourth, the exchange rate may affect FDI inflow. The exchange rate volatility is calculated by using a real effective exchange rate. The higher the volatility, the more unstable the RMB exchange rate is.

The FDI policies of the host country may directly affect the total size and speed of FDI inflow to the host country. The host country policies that affect FDI mainly include Tariff level, trade openness, and related incentive and restrictive policies. With a higher tariff level and lower trade openness, FDI inflow would face greater resistance. On the contrary, a lower tariff level and more preferential treatment of foreign investment would encourage FDI inflow. In this paper, the actual tariff level is calculated by dividing the tariff revenue by the monthly import amount of China, and the preferential treatment of foreign investment is calculated as the difference between the proportion of the operating income of foreign-funded businesses in GDP and the ratio of tax revenue from foreign-funded businesses in the total tax revenue. The two factors are used to measure the extent to which China welcomes FDI inflow.

As for global risks, White and Fan (2006) define them as risks that will have a systemic impact on all countries and all trades on a global scale, including natural disasters, terrorist attacks, wars, financial crises, and epidemic diseases. These crises are hard to predict and can be extremely costly. The COVID-19 is a global risk, which has a huge impact on the development of the global economy and will lead to a decline in FDI inflow. We construct a global risk factor based on the fear index (S&P 500 volatility, or VIX). When VIX is higher than 10% of the 50-day moving average, there is a global crisis in that month, and the value of the global risk factor at this time is 1; otherwise, it is 0.

Table 1. Description of Model Variables

Variables	Indicators	Construct	Sign
FDI (Explained Variable)	Effects of COVID-19 on FDI Inflow to China	FDI used in China	
Global Economic Sentiment	NYSE	Calculated as the monthly growth rate of the month-end New York Stock Exchange Composite Index	Positive
China's Economic Growth Rate	GDP	Converted to monthly data for calculating the monthly growth rate	Positive
Interest Rates	US 10-year Debt Rates	US 10-year treasury notes yield	Negative
Chinese Stock Market Activity	Shanghai Stock Exchange's Tradable Market Capitalization MV	The monthly tradable market capitalization of the Shanghai Stock Exchange	Positive
RMB Exchange Rate Stability	Real Exchange Rate Volatility (%) Volatility ER	RMB real exchange rate volatility	Negative
Trade Openness	Real Tariff (%) Tariff	Tariff revenue/Chinese imports	Negative
Incentive Policies	Preferential Treatment for Foreign Investment (%) TR	(Operating Income of foreign-funded businesses/GDP) - (Tax from foreign-funded businesses/Total tax)	Positive
Global Risk Factor	Global Risk	S&P 500 Volatility (US: VIX)	Negative

The data for 234 monthly observations for the period October 2002–March 2022 are collected from the National Bureau of Statistics of China, Wind Database, and Pandas Database. For the GDP-related calculations, the quarterly GDP data are converted to monthly data, and missing data are supplemented with the monthly mean of the next period. We also calculate the month-on-month growth rate for NYSE and GDP. Moreover, it should be noted that the FDI inflow unit is converted from USD to CNY(the exchange rate is 0.1500 USD/CNY).

3.2. Model Development

The following model is constructed for the above economic variables and dummy variables, where economic variables are lagged by one period and the global risk factor is synchronized with the explained variable to measure the real-time impact:

$$FDI_t = f\{Economic\ Determinants_{t-1}, Global\ Risk_t\} \tag{1}$$

As an integrated regression algorithm, XGBoost is used for data training and prediction, which is a widely-used boosting algorithm. General boosting techniques use classification and a regression tree. A tree can be decomposed into numerous leaves, each of which can be scored according to the weight of a specific feature, or the extent to which the feature affects the explained variable. XGBoost enhances general Boosting by adding more trees, enabling it to classify numerous input variables consistently and improve the model accuracy. In effect, each addition of a tree is enabling the learning of a new function to fit the residual term of the last prediction. The final prediction result is the sum of each tree's scores of the leaf nodes. As one of the Tree Ensemble models, it also adds a regularization term to the objective function to control the complexity of the model so as to prevent overfitting. This is also a feature of XGBoost over the traditional gradient boosted decision tree. The objective function of XGBoost is as follows:

$$Obj(\theta) = \sum_{i}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Phi(f_k) \tag{2}$$

Where $\Phi(f_k)$ is the regularization term, reflecting the number of leaf nodes of the tree and the sum of squares of the weight of each leaf. As the XGBoost model needs to refer to the learning result of the last round in the new round of learning, that is, the prediction result of the *t* time will retain the model prediction of the *t-1* time and add new observations. The predicted value of the model is iterative, as shown below:

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{3}$$

Taking the sum of squares of residuals as the objective of minimization optimization, the objective function is derived by incorporating the objective as follows:

$$\begin{aligned} Obj(\theta) &= \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \Phi(f_t) \\ &= \sum_{i=1}^{n} \left(y_i - \left(\hat{y}_i^{(t-1)} + f_t(x_i)\right)\right)^2 + \Phi(f_t) + Constant \end{aligned} \tag{4}$$

The ultimate goal is to find the score value of each feature f_t that minimizes the cost function.

The sample data are mainly trained and tested by Python and machine integrated learning, and the training effect of the model is evaluated by cross-validation. Relevant data are imported into the machine learning library, 85% of the sample data are selected as the training set, 15% as the test set. After that, max-depth=2 and n-estimators=50 are chosen in the model parameter to optimize the model performance.

To evaluate the performance of the XGBoost model, the sklearn.metrics algorithm is invoked in Python and the results are presented in Table II. Evaluation indicators on test set such as explained variance, root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination R squared show that the overall performance of the XGBoost model is satisfactory.

Table 2. Evaluation Indicators of XGBoost Model

Model Evaluation Indicators	Explained Variance	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	R^2
XGBoost Model	0.5338	142.7029	116.5230	0.5337

As shown in Fig. 1 below, for most samples, the prediction of the model on the test set generates results very close to the actual value, indicating that the fitting of the XGBoost model is very satisfactory.

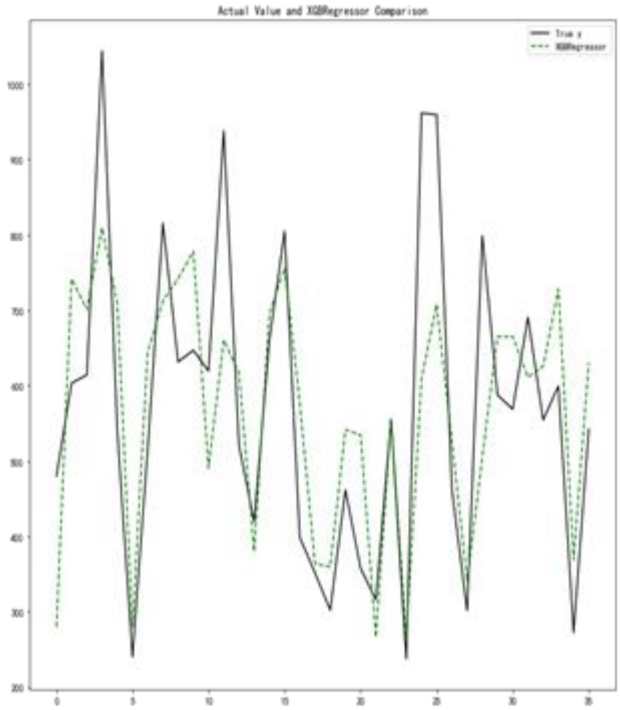

Figure 1. XGBoost's Predicted Value Fitting with Actual Value of Test Set

(Note: The horizontal axis denotes month and the vertical axis denotes the size.)

3.3. Stress Test

The XGBoost model is used to simulate and forecast the FDI from 2020 to 2022 based on the year's actual data of the explanatory variables. The results are shown in Table III. The actual FDI inflow to China in 2020 is CNY 2,513.55 billion, while the total predicted FDI is CNY 2,498.40 billion, which is about 0.60% lower than the actual value. The result implies that the model has outstanding predictive performance and China's relatively effective measures in the face of COVID-19 may have enhanced the positive mechanism of the COVID-19 on FDI and thus, enabled them to overcome the adverse factors effectively. The net effect is the increased size of FDI inflow.

Table 3. Comparison of Actual and Predicted Foreign DIRECT INVESTMENT Inflow to China during January 2020–March 2022 (CNY 0.1 billion)

Period	Actual Value	Predicted Value
2020Q1	2,080.51	2,183.02
2020Q2	2,449.27	2,374.90
2020Q3	2,355.91	2,399.85
2020Q4	2,741.34	2,684.04
2021Q1	2,991.40	2,869.49
2021Q2	3,074.09	2,988.62
2021Q3	2,553.96	2,788.21
2021Q4	2,948.72	2,984.66
2022Q1	3,940.30	3,721.20
Total	25,135.49	24,983.99
Loss Rate		-0.60%

Data sources: National Bureau of Statistics of China, Wind database, and XGBoost Model Fitting.

To better assess the impact of COVID-19 on FDI inflow, we carry out a stress test based on the data of eight explanatory variables from 2020 to 2022 with the XGBoost regression tree model, covering three stress test scenarios: low-stress, moderate-stress, and high-stress, descriptions and corresponding explanatory variables of which are shown in Table IV. The low-stress scenario is as follows: the pandemic had been contained without causing heightened global investment risks, and the data for the explanatory variables are adjusted by 5% accordingly. The moderate-stress scenario is deemed as: the pandemic had not been contained effectively with increased fear index and heightened global investment risks, and the data for the explanatory variables are adjusted by 8% accordingly. The high-stress scenario is set as: the pandemic spread further with a surge in the fear index and exacerbated global investment risks, and the data for the explanatory variables are adjusted by 10% accordingly.

Table 4. Effects of COVID-19 on Foreign direct investment Inflow under Three Stress Scenarios

Degree of Stress	Description of the Scenario	Changes in Explanatory Variables
Low-stress	The pandemic had been contained without causing heightened global investment risks.	The positive indicators are adjusted down by 5 percent, while the negative indicators are adjusted up by 5 percent.
Moderate-stress	The pandemic had not been contained effectively with increased fear index and heightened global investment risks.	The positive indicators are adjusted down by 8 percent, while the negative indicators are adjusted up by 8 percent.
High-stress	The pandemic spread further with a surge in the fear index and exacerbated global investment risks.	The positive indicators are adjusted down by 10 percent, while the negative indicators are adjusted up by 10 percent.

With adjusted data of explanatory variables for the above three stress test scenarios and the XGBoost regression tree model, the changes in the FDI inflow to China under different stress levels can be obtained. Under the low-stress scenario, the loss rate of FDI in China is 5.71%; under the moderate-stress scenario, the loss rate of FDI in China is 8.49%; under the high-stress scenario, the loss rate of FDI in China is 11.28%. See Table V and Fig. 2 for details.

Table 5. 2020-2022 Foreign direct investment in China and Three Stress Test Scenarios (cny 0.1 billion)

Month	Actual Value	Low-stress	Moderate-stress	High-stress
01/2020	845.54	739.13	547.02	547.02
02/2020	449.44	498.07	549.54	659.26
03/2020	785.53	711.72	605.67	613.91
04/2020	676.17	571.52	595.24	580.84
05/2020	658.16	668.67	668.67	654.27
06/2020	1,114.94	788.52	794.17	680.09
07/2020	603.48	663.98	669.63	699.80
08/2020	802.20	827.21	727.20	760.92
09/2020	950.23	777.47	777.47	801.19
10/2020	788.86	766.46	790.18	712.58
11/2020	958.90	819.98	843.70	727.12
12/2020	993.58	914.57	876.89	853.03
01/2021	898.22	818.73	822.79	712.29
02/2021	840.21	826.09	744.47	573.93

03/2021	1,252.97	1,115.82	1,111.14	941.85
04/2021	943.56	847.78	808.90	805.21
05/2021	838.21	913.76	881.63	865.08
06/2021	1,292.32	995.25	926.92	923.23
07/2021	650.83	899.12	879.46	879.46
08/2021	870.88	983.04	945.36	945.36
09/2021	1,032.25	1,022.37	981.97	992.64
10/2021	850.21	1,042.35	1,001.95	1,001.95
11/2021	1,012.91	1,046.76	1,006.36	1,006.36
12/2021	1,085.60	1,028.07	1,072.47	1,072.21
01/2022	1,056.26	1,147.29	1,147.29	1,147.29
02/2022	1,468.36	1,023.72	983.32	1,007.04
03/2022	1,415.68	1,243.26	1,243.26	1,135.12
Total	25,135.49	23,700.71	23,002.67	22,299.05
Loss Rate		-5.71%	-8.49%	-11.28%

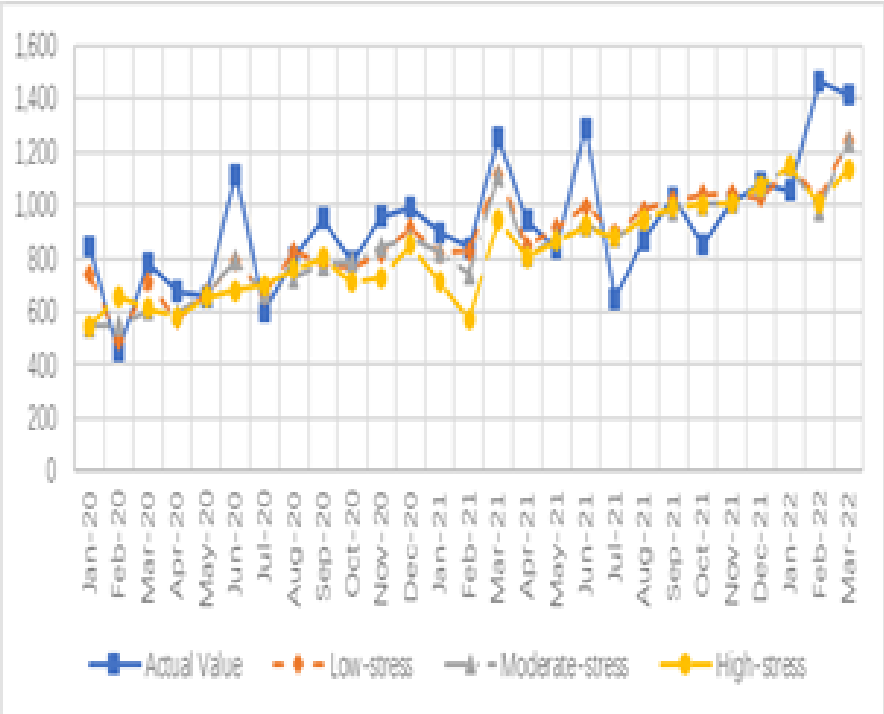

Figure 2. January 2020-March 2022 Foreign Direct Investment in China under Three Stress Test Scenarios (CNY 0.1 Billion)

The test results show that under the low to high-stress scenarios of COVID-19, the loss rate of the FDI inflow to China from January 2020 to March 2022 could reach 5.71%–11.28%, but the actual value is higher than these predicted values. The outstanding FDI inflow could be explained by China's successful pandemic control measures and a series of macro-control policies and measures targeting the pandemic, including providing policy support to businesses and individuals hit hard by the pandemic as well as enhancing openness comprehensively. These measures counter the weight on China's economic growth and considerably improve China's attractiveness to global FDI. The inflow of flight capital suggests that China has been regarded as an important haven and ideal target for global FDI. In summary, under the COVID-19 pandemic, China not only effectively suppresses negative impact mechanisms, but also enhances the role of positive mechanisms, and the net effect is a satisfactory inflow of FDI to China.

3.4. Model Out-of-sample Predictive Performance Comparison

To verify whether XGBoost model can predict the out-of-sample data accurately, it is compared with BayesianRidge, ElasticNet, SVR, ARD regression, and Linear regression five regression models. See Fig. 3 and Table VI for details.

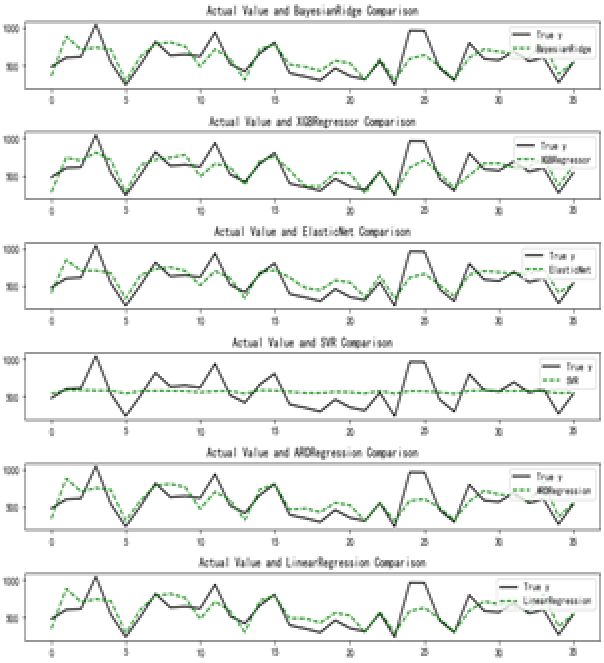

Figure 3. Actual and Predicted Value Comparison of Six Models

Table 6. Out-of-sample Predictive Performance of Six Models

Model Evaluation Indicators	Explained Variance	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)	R^2
XGBoost	0.5338	142.7029	116.5230	0.5337
BayesianRidge	0.4795	151.6420	121.7269	0.4735
ElasticNet	0.4960	150.4789	127.4368	0.4816
SVR	0.0990	198.3698	152.3204	0.0990
ARD Regression	0.4567	154.7832	121.5723	0.4515
Linear Regression	0.4682	153.1132	121.3246	0.4632

It can be found that XGBoost model has the best out-of-sample prediction performance among six models, so the validity and robustness of using XGBoost model to have stress test is proved.

4. Conclusions

This paper summarizes the factors affecting FDI inflow to China based on a literature review and then proposes the positive and negative influence mechanism of the pandemic on FDI inflow to China. An XGBoost tree regression model is employed to examine the correlation between the actual monthly data of FDI and the global risk factor that represents the pandemic's effects and other economic variables, including RMB exchange rate, treasury note rate, GDP growth rate, and tax concessions. A stress test for three different scenarios simulating the pandemic's effects on the FDI inflow to China is also carried out. Results show that under the moderate to high-stress scenarios of the rampant COVID-19 pandemic as well as increasing fear index and global investment risks, as an important destination for FDI inflow, China could have been suffered substantially from the pandemic in terms of FDI inflow to China. From January 2020-March 2022, the loss in China's annual FDI inflow could have reached 5.71%–11.28%, while the country's actual annual FDI inflow is much higher. The results can be mainly explained by the measures adopted by the Chinese government, including pandemic-fighting measures that are prompt and effective, targeted macroeconomic regulation policies, and enhanced openness. They make a rapid recovery or even improvement in China's economic fundamentals, which in turn enhances China's attractiveness to global FDI, more than offsetting the negative impact of COVID-19 on FDI inflow to China.

At present, with the rampant global COVID-19 pandemic, among increasing downside risks to the global economy and heightened pressure to reverse globalization, the negative impact on FDI inflow to many countries would persist. To further effectively prevent and mitigate the negative impact of COVID-19, it is necessary to continue effective response measures. This paper's results suggest that effective pandemic prevention measures and sustained growth of the macroeconomy could enhance FDI inflow and vice versa. Therefore, for many countries, in addition to taking effective measures to prevent the pandemic, effective fiscal and monetary policies should be adopted to maintain stable economic growth, keep a good economic and trade environment, and create a sound environment for economic development, thereby maintaining and enhancing attraction to global FDI. In terms of economic and industrial structure adjustment, it is necessary to keep an eye on the financial needs of industries such as biotechnology and health industries, promoting the development of these industries with policy dividends. The pandemic has underlined the importance of health care, digital biotechnology, and other green industries. The pull effects from the demand side will further increase the share of these industries in the global investment volume. Governments could introduce incentive policies for these industries to promote FDI growth in them as appropriate.

References

[1] M. Jaworek, W. Karaszewski, and M. Kuczmarska, "Pandemic risk: doesn't it really matter? Foreign direct investment after COVID-19," Ekonomia i Prawo. Economics and Law, 2020, vol. 19, no. 2, pp. 275–290.

[2] Z. Y. Hu, "Determinants of FDI Inflows– A case study of China," Foreign Affairs Review, 2006, vol. 23, no. 3, pp. 89–95.

[3] C. White and M. Fan, Risk and Foreign Direct Investment, 1st ed., vol. 1. New York: Palgrave MacMillan, 2006, pp. 35–39.

[4] J. Xu, "Deglobalization Movements and Globalization Transition," International Studies, 2017, vol. 59, no. 3, pp. 1–15+125.

[5] A. Giroud and I. Ivarsson, "World Investment Report 2020: International production beyond the pandemic," Journal of International Business Policy, 2020, vol. 3, pp. 465–468.

[6] M. Alkahtani, M. Omair, Q. S. Khalid, G. Hussain, and I. Ahmad, "A COVID-19 Supply Chain Management Strategy Based on Variable Production under Uncertain Environment Conditions," International Journal of Environment Research and Public Health, 2021, vol. 18, pp. 1662. https://doi.org/10.3390/ijerph18041662.

[7] J. Hu, "The impact of the latest developments on the utilization of foreign direct investment in China and countermeasures," China Economic & Trade Herald, 2021, vol. 38, no. 1, pp. 22–24.

[8] Z. H. Sun and H. X. Wang, "New Characteristics and Influence of International Capital Flow under the Financial Crisis," Practice in Foreign Economic Relations and Trade, 2009, vol. 27, no. 3, pp. 9-11.

[9] M. Ucal, K. M. Özcan, M. H. Bilgin, and J. Mungo, "Relationship between financial crisis and foreign direct investment in developing countries using semiparametric regression approach," Journal of Business Economics and Management, 2010, vol. 11, pp. 20–33.

[10] Y. Chen, "The Influence of Epidemic Situation of COVID-19 to the Investment of Shandong Province in 2020 and the Countermeasures," Shandong Social Sciences, 2020, vol. 34, no. 4, pp. 31–37.

[11] M. O. Moore, "Determinants of German manufacturing direct investment in manufacturing industries," Weltwirtschaftliches Archive, 1993, vol. 129, pp. 120–138.

[12] H. F. Jin, Y. J. Jian, and L. X. Chen, "The Impacts of International Financial Crises on China's FDI:Mechanism and Countermeasures," Contemporary Finance & Economics, 2010, vol. 31, no. 2, pp. 105–112.

[13] J. Zhang and X. Liao, "Impact of the Epidemic about COVID-19 on Global FDI and Development Ideas of Shanghai's Foreign Investment," Scientific Development, 2020, vol. 13, no. 5, pp. 64–70.

[14] J. Zhan, "COVID-19 and investment—an UNCTAD research round-up of the international pandemic's effect on FDI flows and policy," Transnational Corporations (UNCTAD), 2020, vol. 27, no. 1, pp. 25–29.

[15] E. Asiedu, "Foreign Direct Investment in Africa: The Role of Natural Resources, Market Size, Government Policy, Institutions and Political Instability," World Economy, 2006, vol. 29, no. 1, pp. 63-77.

[16] M. A. Gonzalez-Perez, M. Mohieldin, G. T. M. Hult, and J. Velez-Ocampo, "COVID-19, sustainable development challenges of Latin America and the Caribbean, and the potential engines for an SDGs-based recovery," Management Research, 2021, vol. 19, no. 1, pp. 22-37. https://doi.org/10.1108/MRJIAM-12-2020-1119.