The Impact of the US-China Trade Conflict on China's Foreign Economic Relations

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Abstract. On 9 March 2018, in order to impose tariffs of 25% and 10% on imported steel and aluminum, the US government approved a tariff decree, marking the trade conflict between the US and China broke out. It is a turning point in the long-standing trade tensions between the two countries. The US government has taken a series of trade measures against China, mainly due to issues such as trade deficits, intellectual property protection, market access and technology transfer. These elements contributed to the start of the US-China trade dispute starting, have profound effects on the world economy and trading environment. Through an analysis of foreign direct investment (FDI) statistics, this study explores how the trade conflict has affected China's foreign economic relations. The study employs the number of FDI contracted projects and the value of FDI actually utilized from 2010 to 2018 to establish an ARIMA model for forecasting subsequent data. By comparing the predicted values with the actual data post-March 2018, this paper identifies and analyze the discrepancies, providing insights into the trade conflict's effects on China's foreign economic relations.

Keywords: US, Trade conflict, China, Impact, Foreign direct investment, ARIMA model, Forecast.

1 INTRODUCTION

In 2018, the US and China trade conflict started. It has significantly impacted the world economy. Being the two biggest economies in the world, the trade conflict between the US and China is not only about tariffs and trade balance, but also involves a wide range of areas such as technology, intellectual property and geopolitics. From the original disagreement over steel and aluminum tariffs to the application of duties on commodities worth hundreds of billions of dollars against each other, this trade conflict has progressively grown, accompanied by turmoil in international markets and the restructuring of global supply chains. Targeting high-tech companies, China and the US are engaged in an uncooperative tariff game that is costing them welfare losses and hefty tariffs [1]. The conflict between China and the US in this trade conflict has not only profoundly affected the economic development paths of the two countries, but also had a far-reaching impact on the global economic landscape.

It is clear that the trade conflict has a direct effect on bilateral trade. China and the US would lose 0.2% and 1% of their respective GDPs[2]. Tariff barriers between the

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two countries have led to a significant decline in trade volumes, and companies have had to adapt their supply chains and market strategies. Chinese exports have become less competitive in the US market as a result of increased tariffs, when comparing the current trade dispute period to the previous one, the Chinese industries that rely more on import and export to the US are more vulnerable to trade tensions [3]. Chinese overall imports decreased as a result of political unrest, with state-owned businesses suffering the greatest declines and foreign-invested businesses suffering less [4]. The US is confronted with the challenge of pre-tariff import prices that do not decline in response to the implementation of tariffs. Consequently, the full impact of these tariffs is reflected in the duty-inclusive import prices [5]. At the same time, the trade conflict has triggered broader economic effects that have rippled through global supply chains, forcing many multinational companies to reassess their production and sourcing strategies. From the global integrated perspective, trade between China and the US plays a crucial role in dispersing energy resources worldwide and restructuring the integrated energy trade system. It has a significant impact on how other economies use energy throughout the entire supply chain [6]. In addition, the trade conflict has prompted countries to revisit and reorient their international trade policies and to promote the formation of new economic alliances and partnerships.

In the face of high US tariffs, China has taken a variety of countermeasures, including seeking new export markets, increasing investment in the Belt and Road Initiative, and strengthening economic cooperation with other countries and regions. The Belt and Road Initiative lowers trade costs, boosts export companies' earnings, and encourages them to participate in R&D competitions [7]. The trade and investment cooperation between China and the other BRICS countries is resulting in a synergistic effect that is influencing GDP growth [8]. In addition, China has carried out a series of internal economic reforms to enhance the resilience and competitiveness of its economy. The purpose of this study is to discover how China's foreign economic relations are affected by the trade conflict. By analyzing the changes of the foreign direct investment, reveal the far-reaching impact of the trade conflict on China's long-term economic development.

The following section outlines the structure of the remainder of this research: The research design is covered in Part 2 of the publication, along with details on the data source, unit root test, and ARIMA model setup. Part 3 is the empirical results and analyses, includes the fixed-order and predictive results and interpretations. Finally, Part 4 is the conclusion, which summarizes the full text and presents the main findings.

2 RESEARCH DESIGN

2.1 Data Source

The National Bureau of Statistics provides the data, it is an authoritative national data site with comprehensive data on various industries. The data includes the number of contracted FDI projects and the amount of actual utilization of FDI in China from January 2010 to November 2019, with a focus on the fluctuation of the number of projects and the amount involved, both before and after the imposition of tariffs by the US on China in 2018.

2.2 ADF Unit Root Test

Once the model has been finished being built, it is necessary to perform an ADF test. Finding out if there is some smoothness in the data is the aim of the ADF test, and if it is not then the data needs to be differenced. Table 1 makes it clear that the two data groups' log returns have a p-value of 0, or less than 0.1. Consequently, rejecting the null hypothesis that the model is feasible and stable is necessary. It is significant that first-order differencing was used to both collections of data, the purpose of this is to facilitate the subsequent job definition process.

Table 1. ADF test

Variables	t	p
Number of Projects for Contracted FDI		
Ln value	-0.869	0.9594
1st order difference	-6.007	0.0000
Value of FDI Actually Utilized		
Ln value	-4.555	0.0012
1st order difference	-9.260	0.0000

2.3 ARIMA Model

The ARIMA model is a combination of AR model and MA model [9]. The ARIMA model is a traditional time series analysis technique that is used to project values at future points in time. By adjusting the parameters of the model, the time series data's patterns and seasonal fluctuations can be captured by the ARIMA model, thus providing accurate forecasts of future values. In the ARIMA (p, d, q) model:

The relationship between the findings made now and those made in the past is shown by the autoregressive component. The AR model takes values from the past to predict values for the future, if future observations have a linear relationship with past observations. In the AR model, the order (p) represents the number of past time points that are taken into account by the model. The following is the precise mathematical form:

$$x_t = \varphi_0 + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t \tag{1}$$

A non-stationary time series is transformed into a stationary time series using the differencing component. By performing a difference operation on the raw data, trends and seasonality in the data can be eliminated, making the data stationary. The order of differencing (d) denotes the number of iterations of the differencing operation.

The link between the random error term and the current observation is represented by the moving average. The AR model forecasts future values by utilizing historical data. The MA model employs a weighted average of past error terms to forecast future values, provided that future observations exhibit a linear relationship with the aforementioned error terms. The number of historical error factors that the MA model takes into consideration is indicated by its order (q). The following is the precise mathematical form:

$$x_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (2)$$

3 EMPIRICAL RESULTS AND ANALYSIS

3.1 Order of the ARIMA Model

Plotting the ACF and PACF for the log series of the number of projects for contracts FDI and the value of FDI actually utilized will help determine the optimal lag order for the ARIMA model, the plots were employed to ascertain the value of p and q [10], and the results are shown in figure 1.

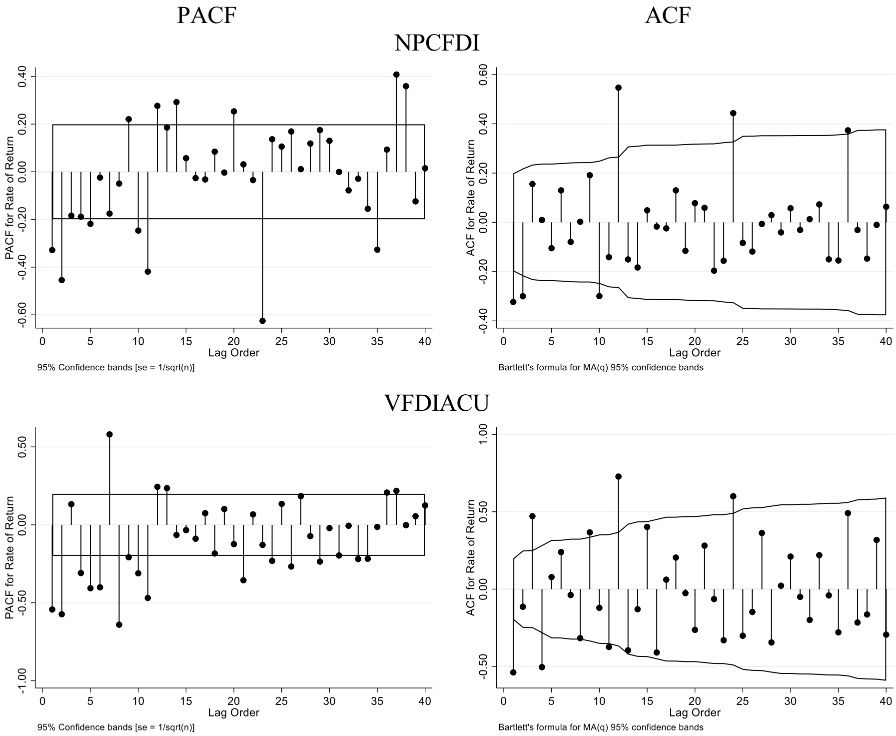

Fig. 1. ARMA (p, q) identification

For ARIMA model, when the ACF plot presents trailing tails and the PACF plot presents truncated tails, the lag term exhibited by the PACF plot represents the optimal value for the AR model order, when the ACF plot presents truncated tails and the PACF plot presents trailing tails, the lag term exhibited by the ACF plot represents the optimal value for the MA model order. According to the ACF and PACF plots above, constructing ARIMA models for the two groups of the data. Once the model has been constructed, the residual test is conducted in accordance with the methodology outlined below:

Table 2. Residual Test

Model	Portmanteau (Q) statistic	Prob > chi2
NPCFDI – ARIMA (10,1,10)	60.0694	0.0216
VFDIACU – ARIMA (10,1,9)	26.7183	0.9467

According to Table 2, the trend features persist even though the value of the FDI actually used data fails the residual test, and the influence of its error terms can be ignored. The ARIMA models for the number of projects for contracted FDI data have been found to pass the residual test, this indicates that the error term is consistent with white noise.

3.2 Forecast Results and Interpretation

Once the model has been constructed and successfully passing the residual test, using Stata to forecast the data after March 2018, the results can be summarized as follows:

Table 3. NPCFDI Forecast Results, ARIMA (10,1,10)

	Actual value	Predicted value	Difference	Percentage	Average
2017-05	2433				
2017-06	2894				
2017-07	2650				
2017-08	2686				
2017-09	3152				
2017-10	2633				
2017-11	4641				
2017-12	4837				
2018-01	5197				
2018-02	3651				
2018-03	5492	3549.846	1942.154	54.71%	
2018-04	4662	4776.536	-114.536	-2.40%	
2018-05	5024	4592.467	431.533	9.40%	
2018-06	5565	4507.081	1057.919	23.47%	
2018-07	5648	4385.674	1262.326	28.78%	
2018-08	6092	5311.595	780.4047	14.69%	
2018-09	4591	4455.409	135.5912	3.04%	
2018-10	3623	3767.244	-144.244	-3.83%	
2018-11	5158	5053.198	104.8021	2.07%	
2018-12	5830	5870.915	-40.9152	-0.70%	12.92%

Table 3 and 4 provide the actual and predicted values, the difference between the two values, the percentage difference relative to the actual value as well as the average percentage difference between the two values of the number of FDI contracted projects and the value of FDI actually utilized.

Table 4. VFDIACU Forecast Results, ARIMA (10,1,9)

	Actual value	Predicted value	Difference	Percent-age	Average
2017-05	8113				
2017-06	14801				
2017-07	6495				
2017-08	9363				
2017-09	10585				
2017-10	9034				
2017-11	18782				
2017-12	11130				
2018-01	12074				
2018-02	8988				
2018-03	13447	9036.888	4410.112	48.80%	
2018-04	9091	9452.987	-361.987	-3.83%	
2018-05	9059	8344.62	714.3805	8.56%	
2018-06	15662	16534.83	-872.826	-5.28%	
2018-07	7749	8774.795	-1025.79	-11.69%	
2018-08	10427	11245.34	-818.335	-7.28%	
2018-09	11462	11936.78	-474.781	-3.98%	
2018-10	9696	8286.391	1409.609	17.01%	
2018-11	13602	15253.92	-1651.92	-10.83%	
2018-12	13709	10123	3586.001	35.42%	6.69%

Table 3 shows that, for the month of March 2018, the actual value was 5492, while the predicted value was 3549.846, a difference of 1942.154. The forecast value is much smaller than the actual value, suggesting that the outbreak of the trade conflict led to a rapid growth in the number of contracted FDI projects in the short term. This may be due to the lag in the market's response to policy. Following the start of the trade conflict, the Chinese government have also introduced some policy adjustments targeting foreign investment, such as measures to strengthen regulation and restrict investment in certain areas, and these policy changes have affected the number of foreign direct investment projects.

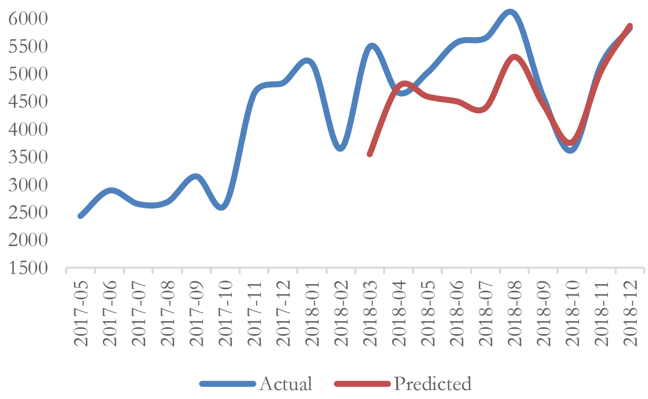

Fig. 2. NPCFDI before and after Covid – 19 (Photo credit: Original)

The predicted value for April and May is relatively accurate, with a small forecast error, indicating that the measures taken by the Chinese government have been relatively effective and that the number of contracted FDI projects has not declined sharply.

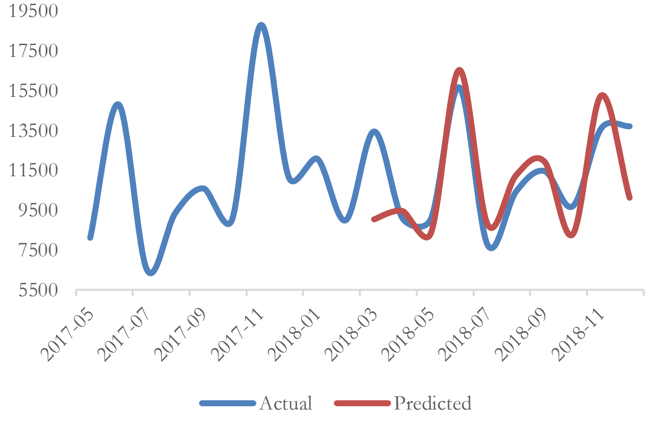

Fig. 3. NPCFDI (Difference, %) after Covid – 19 (Photo credit: Original)

The percentage error for June was 23.47 percent and for July 28.78 percent. The forecast error for these months was also large. The US government published a list of items that would be subject to duties on June 15, 2018, and as a result, imports from China worth about $50 billion would be subject to 25% taxes, of which tariff measures will be implemented on approximately $34 billion of goods from 6 July 2018 onwards. In retaliation, On the same day, China levied a 25 percent import duty on identical-sized US goods. Despite a series of measures taken by the US against China, the actual value did not fall as predicted, but instead remained stable within certain limits.

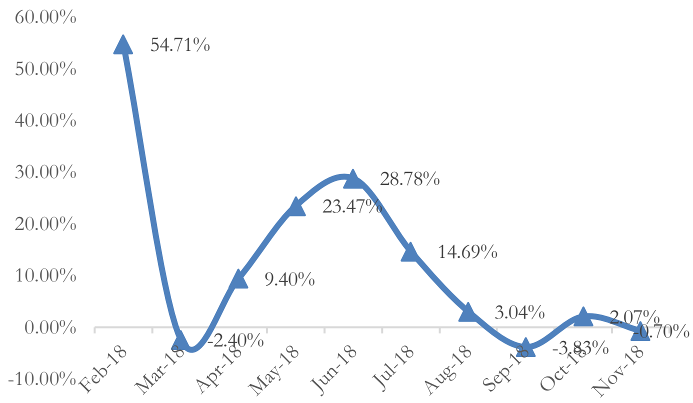

Fig. 4. VFDIACU (Difference, %) and after Covid – 19 (Photo credit: Original)

The trade conflict had an impact on the number of projects for contractual FDI, as shown by Figures 2 and 4. However, the government policies and the market's ability to self-regulate have led to an overall upward trend.

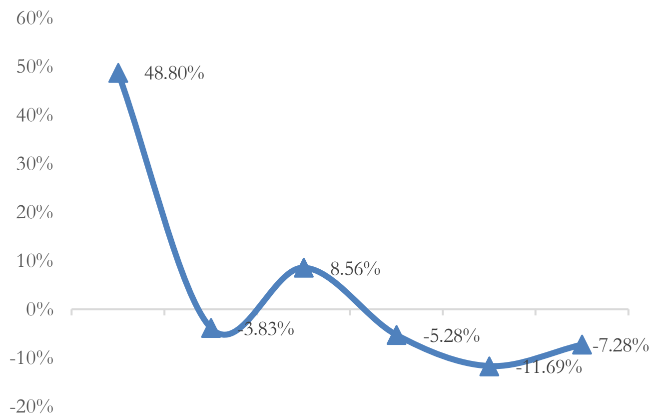

Fig. 5. VFDIACU before and after Covid – 19 (Photo credit: Original)

Table 4 shows that, for the month of March 2018, the actual value was 13447, whereas the projected value was 9036.888, a difference of 4410.112 and a percentage error of 48.8 percent. The reason for such an error is consistent with the above. Besides, the market needs some time to react to the policy, FDI does not immediately fluctuate dramatically, which is also the reason for the large error in the forecast in March. In subsequent forecasts the predicted and actual values are closer, the error is small, and the data shows cyclical fluctuations.

According to the Figure 3 and 5, the value of FDI actually utilized was less affected by the trade conflict. The trend of steadily improving data remains unchanged.

4 CONCLUSION

The object of the paper is to study how China's foreign economic relations have been impacted in the short term against the backdrop of the trade conflict, and to forecast the future direction and development of China's foreign economic relations. The study forecasts the number of projects for contracts FDI and the value of FDI actual utilized by using the ARIMA model. According to the forecast results, China's foreign economic relations have been impacted in the short term, but the indicators are still trending upwards, China's foreign economic relations have not been stalled by the US-China trade conflict.

All things considered; China's foreign economic relations have been significantly impacted by the ongoing trade conflict. The trade conflict has not only exacerbated trade tensions, but also prompted China to accelerate its multilateral cooperation and independent development. In response to the trade conflict, China has gradually shifted its externally dependent development model, strengthened economic cooperation with other countries, and pushed for more bilateral and multilateral trade agreements. Although the trade conflict has posed certain challenges to China, it has also prompted China to accelerate the pace of economic restructuring and reform, and has enhanced China's position and influence on the global economic stage. In the future, China will continue to commit itself to building an open economic system, strengthening international cooperation and promoting the stability and prosperity of the global economy.

REFERENCES

1. Jiandong Ju, Hong Ma, Zi Wang, Xiaodong Zhu. Trade wars and industrial policy competitions: Understanding the US-China economic conflicts. Journal of Monetary Economics,141,42-58(2024).
2. Abdul Abiad, Kristina Baris, John Arvin Bernabe, Donald Jay Bertulfo, Shiela Camingue-Romance, Paul Neilmer Felicsiano, Mahinthan Joseph Mariasingham, and Valerie Mercer-Blackman. The Impact of Trade Conflict on Developing Asia. Asian Development Bank Economics Working Paper Series, No.566, (2019).
3. Yanhua Chen, Athanasios A. Pantelous. The U.S.-China trade conflict impacts on the Chinese and U.S. stock markets: A network-based approach. Finance Research Letters, 46(B),(2022).
4. Yuhua Li, Ze Jian, Wei Tian, Laixun Zhao. How political conflicts distort bilateral trade: Firm-level evidence from China. Journal of Economic Behavior & Organization. 183, 233-249(2021)
5. Pablo D Fajgelbaum, Pinelopi K Goldberg, Patrick J Kennedy, Amit K Khandelwal. The Return to Protectionism. The Quarterly Journal of Economics, 135(1), 1–55(2020).
6. Yilin Li, Bin Chen, Chaohui Li, Zhi Li, Guoqian Chen. Energy perspective of Sino-US trade imbalance in global supply chains. Energy Economics, 92,(2020)
7. Kai A. Konrad. China’s public international investment: A strategic-trade-policy perspective. Economic Modelling, 139,(2024)
8. Svetlana Gusarova. Role of China in the development of trade and FDI cooperation with BRICS countries. China Economic Review,57,(2019).

9. M. A. A. Amin and M. A. Hoque. Comparison of ARIMA and SVM for Short-term Load Forecasting. 2019 9th Annual Information Technology, Electromechanical Engineering and Microelectronics Conference (IEMECON),1-6, (2019).
10. Fuad Ahmed Chyon, Md. Nazmul Hasan Suman, Md. Rafiul Islam Fahim, Md. Sazol Ahmmed. Time series analysis and predicting COVID-19 affected patients by ARIMA model using machine learning. Journal of Virological Methods, 301(2022).