

# The impact of Sino-US trade conflict on Chinese Manufacturing: Evidence from Time Series Model

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**Abstract.** In April 2018, the trade conflict between China and the United States broke out, and major economic markets in China were hit. As an industry that dominates China's stock market, China's manufacturing industry's index fluctuations are enough to attract attention. It is even related to whether the Chinese government needs to implement corresponding strategies for it. In order to explore the impact of the Sino-US trade conflict on China's manufacturing market, this paper uses GARCH and ARMA-GARCH model to estimate this shock. From the estimation results of exogenous variables, it can be seen that in the long term, the US imposition of tariffs on China has no significant positive impact on the volatility of China's manufacturing industry. These results prove that China's economy still has a considerable degree of anti-risk capability in the long term in the face of external shocks. Therefore, the Chinese government does not need to worry too much about the impact of tariff increases on Chinese manufacturing.

**Keywords:** US-China trade war, Chinese manufacturing, ARMA-GARCH Model.

## 1. Introduction

On April 4, 2018, the U.S. government announced the list of goods to be subject to additional tariffs, which will impose 25% tariffs on 1,333 items worth \$50 billion worth of Chinese exports to the United States. Although China and the United States reached a consensus through negotiations, they failed to resolve the conflict. On July 6, the U.S. government announced that the first part of the U.S. tariff list on China will come into effect from 0:01 EST on that day, which covers imports of Chinese goods worth about \$34 billion. The trade war between China and the United States has officially started. On September 18, 2018, US President Trump announced a 10% increase in tariffs on \$200 billion of Chinese products, which will be implemented on September 24. Trump has since announced additional tariffs on China on May 6 and August 1, 2019.

A trade war that began against China's unfair economic policies has turned into a "Cold War". The United States has modified its international economic policy under President Donald Trump because his obsession with trade deficits prompted him to impose punitive tariffs on China, to be specific, he significantly increased tariffs on China's products. The United States has adopted a protectionist policy toward China, its main trading partner, since 2018. Subsequently, the bilateral relationship between the two nations deteriorated, and the United States started a trade war with China, reversing its long-standing leading role in global market integration. According to statistics from the International Trade Center (ITC, 2020), bilateral trade between these nations was \$683 billion in 2018, with US exports and imports being \$120 billion and \$563 billion, respectively. In addition, the United State had imposed tariffs on \$350 billion worth of Chinese imports. As a result of the tariffs, China's access to high-tech United States products was constrained, also it was foreign investment involved security concerns, as well as complaints of unfair commercial practices in China. Afterward, China had responded with taxes on \$100 billion worth of US exports by late 2019. As a major global event, this conflict has attracted the attention and discussion of many scholars.

Most of the literature on the China-United States trade conflict in 2018 now focuses on the global economic impact and the analysis of the strategic level between China and the United States, but little attention is paid to the impact of the China-US trade war on various economic markets in China, especially in manufacturing. Recent research showed that the outbreak of the trade war between China and the United States stems from the serious threat of the rapid rise of China in all aspects to the hegemony of the United States [1]. In order to slow the growth of China's military [2, 3] and economic

power [4], the bilateral trade constraints have become a powerful tool [5]. Author Chad P. Bown analyzes the strategic significance of the trade war between China and the United States in the article [6]. Another research also proves that, for China, its best option is to maintain the status quo, and any further aggressive policies and actions will make the situation worse [7]. Although the start of this trade war does not have many options for China, it is necessary to understand its impact. According to the article by Eddy Bekkers and Sofia Schroeter, tariff increases have less impact on the global economy [8]. However, there is no detailed analysis of the impact on China's economic market. Recent research showed that industrial equipment manufacturing dominates the Chinese stock market, while manufacturing has a central role in the U.S[9]. Therefore, the analysis of the impact on the manufacturing market is important which China should pay more attention to and even change strategies accordingly.

This paper contributes in several aspects. It will analyze the time-varying impact of the trade war between China and the United States on Chinese manufacturing by using different models. In order to visualize its impact of it, it combed the timeline of the trade war and collected manufacturing index data from 3 months before the start of the trade conflict to before the outbreak of the COVID-19. To better demonstrate the relationship between the two, it will analyze the data through the use of the model and compare it to a timeline. It shows how various events have caused volatility in manufacturing indices during the trade war. Finally, it showed the trend of analyzing the future manufacturing market under the given data, and further analysis suggests the direction of China's manufacturing market under the trade conflict between China and the United States.

The following parts of the paper are organized as follows: Part 2 is the research design, which concludes data sources, unit root test, and model specification. Part 3 is empirical results, including GARCH and ARMA-GARCH model estimation results. Part 4 is discussion and Part 5 is conclusion.

## 2. Research Design

This section will present the overall research design. The source of the data will be introduced first and its reliability will be verified. Next, this paper will perform ARMA ordering on the usage data. Finally, this part will introduce the ARMA-GARCH model setting and explain the dummy variables.

### 2.1 Data Sources

To examine the impact of the China-US trade war on China's manufacturing industry, it is obvious that it needs China's manufacturing index data and look for whether the data fluctuations during the trade war are related to the major events of the trade war. So, It chose "Investing.com" to download the closing prices of the China Manufacturing Index and make it a time series. Since "Investing.com" is one of the top three global financial websites in the world, the data it provides is credible and authoritative. Regarding the choice of time, in order to prevent the impact of COVID-19 on the data, the available data will be from before the start of the Sino-US trade conflict to before the full outbreak of COVID-19, which is, started on 2018/01/02 and ended in 2020/02/28. In order to ensure the accuracy of the calculation, It also obtained the logarithmic manufacturing index and logarithmic rate of return through the calculation.

### 2.2 Unit Root Test

$$y_t = by_{t-1} + a + \varepsilon_t \quad (1)$$

When using time series models, the time series is required to be stationary. The commonly used strict statistical test method is the Augmented Dickey-Fuller test. A unit root is defined while the lag term coefficient  $b$  is 1 according to formula 1. The link between the independent and dependent variables is deceptive when the unit root exists, because any error in the residual series does not decrease as the sample size grows, implying that the residual effect in the model is permanent. The

ADF test is used to see if a sequence has a unit root: if the sequence is stationary, there isn't one. As a result, the ADF test's H0 hypothesis is that there is a unit root. If the obtained significance test statistic is less than three confidence levels (10%, 5%, 1%), the null hypothesis is rejected with (90%, 95%, 99%) confidence.

Since it needs to be modeled with a time series, the first is to determine the data's stationarity. By using the ADF-test on the three-time series manufacturing Index, logarithmic manufacturing index, and logarithmic rate of return, it got Table 1.

Table 1 ADF-test

Variables	t-statistic	p-value
Manufacturing index	-1.651	0.7719
Logarithmic manufacturing index	-1.607	0.7899
Logarithmic rate of return	-15.977	0.0000***

Note: The 1%, 5% and 10% thresholds are  $t=-3.960$ ,  $t=-3.410$  and  $t=-3.120$ .

Table 1 showed that only the logarithmic rate of return's t-value = -15.977 is greater than -3.120 which is a critical value of 10% that it can reject the H0 which the original series is not the stationary series. So only the time series of the logarithmic rate of return is good to use for prediction.

### 2.3 ARMA Model

In order to obtain predictions for the future from the data, it, therefore, needed to introduce a model setting ARMA model. It is able to predict future values from past realized values and past disturbance terms.

$$X_t = c + \varepsilon_t + \sum_{i=1}^p \varphi_i X_{t-i} + \sum_{i=1}^q \theta_i \varepsilon_{t-i} \quad (2)$$

According to the formula, p is the order of the autoregressive polynomial and q is the order of the moving average polynomial.  $\varphi$  is the autoregressive model's parameters.  $\theta$  are the moving average model's parameters. For the rest, c is a constant, and  $\varepsilon$  are error terms (white noise).

$$\rho_k = \frac{Cov(x_t, x_{t-k})}{\sqrt{Var(x_t)Var(x_{t-k})}} = \frac{Cov(x_y, x_{t-k})}{Var(x_t)} = \frac{\gamma_k}{\gamma_0} \quad (3)$$

The set  $\{\rho_x\}$  composed of autocorrelation coefficients is called the autocorrelation function (ACF) of  $x_t$ . It is a function of the similarity between two observations versus the time difference between them.

$$x_t = \phi_{0,1} + \phi_{1,1}x_{t-1} + \varrho_1 \quad (4)$$

$$x_t = \phi_{0,2} + \phi_{1,2}x_{t-1} + \phi_{2,2}x_{t-2} + \varrho_2 \quad (5)$$

$$x_t = \phi_{0,3} + \phi_{1,3}x_{t-1} + \phi_{2,3}x_{t-2} + \phi_{3,3}x_{t-3} + \varrho_3 \quad (6)$$

...

The partial autocorrelation function (PACF) of stationary time series is a function of ACF, which is a useful tool in ordering AR models. It has the following properties: when the sample size T tends to infinity,  $\hat{\phi}_{p,p}$  converges to  $\phi_p$ ; for  $q > p$ ,  $\hat{\phi}_{t,t}$  converges to 0; for  $q > p$ , the asymptotic variance of  $\hat{\phi}_{t,t}$  is  $\frac{1}{T}$ .

By using PACF and ACF to find the order of the ARMA model, it got Figure 1 which p=20 and q=39. Since MA (39) was hard to run out, it had been removed.

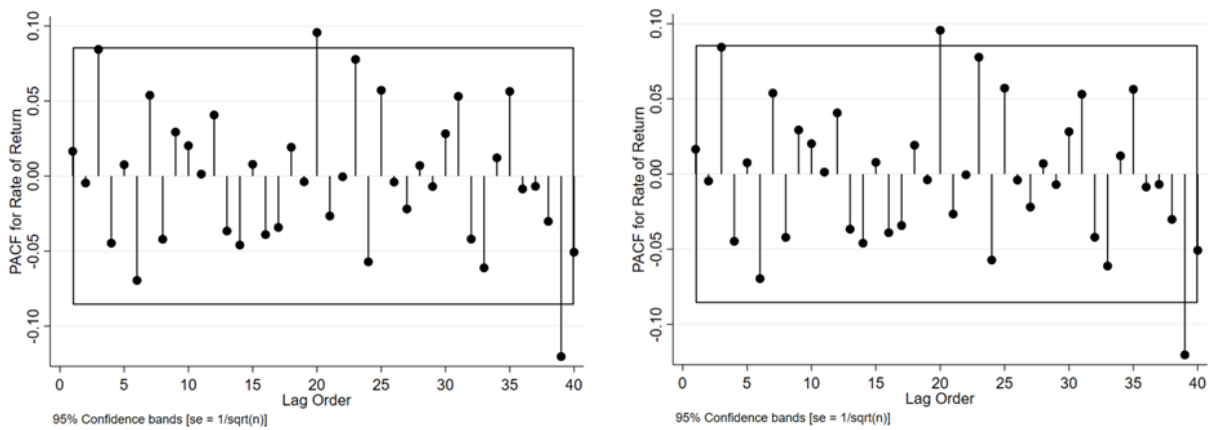


Figure 1 PACF and ACF for ARMA identification

### 2.4 ARMA-GARCH Model

The ARMA-GARCH Model is a model that can predict both returns and volatility. Before using the model, it first needed to test the data for conditional heteroskedasticity. Figure 2, it showed that the data used, the time series of the logarithmic rate of return has conditional heteroskedasticity, so it can model GARCH and ARMA-GARCH.

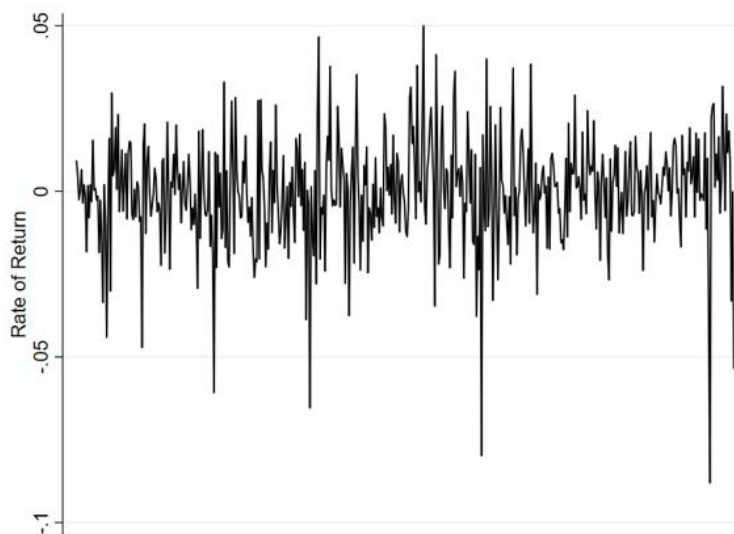


Figure 2 Rate of return

The GARCH model is mainly composed of two parts, the mean equation, and the variance equation. The ARMA-GARCH Model is based on the GARCH Model, and the mean equation is replaced by the ARAM Model, and the variance equation is this formula:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i a_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (7)$$

To ensure that the conditional variance is non-negative, it needed to be set  $\alpha_0 > 0$ ,  $\alpha_i \geq 0$ ,  $\beta_j \geq 0$ . In addition, in order to explore the impact of the Sino-US trade conflict on the volatility of the manufacturing index, it also needed to introduce dummy variables in the ARMA-GARCH Model.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i a_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma D \quad (8)$$

In the Sino-US trade war, China and the US have engaged in many political games. In order to restrict China's economic system, the US government's main policy is to announce and implement additional tariffs on China. Therefore, in order to know whether the manufacturing industry, one of China's important systems in the economic market, is affected by it, this paper chose 5 important nodes from 2018/01/02 to 2020/02/28, that is, the 5 tariff increases that the U.S. government officially imposed on China during this period, and wrote them as 5 dummy variables respectively. Since the first tariff increase was on 2018/07/06, It set  $D_1$  equal to 0 for all days from 2018/01/02 to 2018/07/05 and the remaining days equal to 1. Same way, since The US government implemented tariff increases on 2018/08/23, 2018/09/25, 2019/05/11, and 2019/09/01, It set  $D_2$  equal to 0 for all days from 2018/01/02 to 2018/08/22 and remaining days equal to 1,  $D_3$  equal to 0 for all days from 2018/01/02 to 2018/09/21 and remaining days equal to 1,  $D_4$  equal to 0 for all days from 2018/01/02 to 2019/05/10 and the remaining days equal to 1 and  $D_5$  equal to 0 for all days from 2018/01/02 to 2019/08/30 and the remaining days equal to 1.

### 3. Empirical Results and Analysis

#### 3.1 GARCH Model

Table 2 showed the respective coefficients under the influence of different dummy variable combinations and the standard error of each coefficient. The ARCH and GARCH terms are both first-order results. It can see that the coefficients of most dummy variables are not significant, only  $D_4$  is significant at the 1% level and both ARCH and GARCH effects are significant for each column model.

According to the data obtained in Table 2, starting with the ARCH effect, it can be found from the estimation results of the GARCH model that the ARCH effect and GARCH effect of each column of models are significant, indicating that the manufacturing yield has significant ARCH and GARCH effects. That is to say, the time series of logarithmic rates of returns have a serial correlation to conditional heteroskedasticity series. At the same time, from the estimation results of exogenous variables, in the long run, the US tariffs on China have no significant positive impact on the volatility of China's manufacturing industry. However, this result may be caused by the autocorrelation of manufacturing returns, so it is necessary to control this autocorrelation in the mean equation for further verification. From this, it chose the ARMA-GARCH Model for further calculations.

Table 2 GARCH model estimation results

Variables	(1)	(2)	(3)	(4)	(5)
D1	0.0118 (0.1953)	-0.2940 (0.7934)	-0.2420 (0.7612)	-0.1177 (0.6128)	-0.1192 (0.6152)
D2		0.3305 (0.7813)	-0.0683 (1.2105)	-0.1998 (0.9689)	-0.1945 (0.9696)
D3			0.3886 (0.8694)	0.8949 (0.6920)	0.8925 (0.6910)
D4				-0.7447*** (0.1858)	-0.7030*** (0.2546)
D5					-0.0730 (0.3008)
ARCH (-1)	0.1502*** (0.0273)	0.1521*** (0.0281)	0.1521*** (0.0293)	0.1419*** (0.0251)	0.1443*** (0.0271)
GARCH (-1)	0.7442*** (0.0526)	0.7402*** (0.0539)	0.7301*** (0.0569)	0.6654*** (0.0759)	0.6625*** (0.0763)
Constant	-10.3831*** (0.3081)	-10.3650*** (0.3090)	-10.3089*** (0.3082)	-9.9745*** (0.3139)	-9.9691*** (0.3112)

### 3.2 ARMA-GARCH Model

In order to control for autocorrelation in the model mean equation, after the GARCH Model, it still did the calculations via the ARMA-GARCH Model.

Compared with Table 2, Table 3 also calculated the coefficients of the mean equation. The coefficients under the 20th-order AR model are all insignificant. In the variance equation, the coefficients of the dummy variables are still only significant for  $D_4$ , and the rest are insignificant. ARCH, GARCH, and constant term coefficients are also significant.

According to Table 3, from the estimation results of ARMA-GARCH, when the autocorrelation is controlled in the mean equation, the ARCH and GARCH effects of the model are still significant. In addition, the results of exogenous variables show that they still have no significant impact on China's manufacturing index. The increase in the series of tariffs imposed by the United States on China during the Sino-US trade conflict has not caused volatility in China's manufacturing index yields.

**Table 3** ARMA-GARCH model estimation results

Variables	(1)	(2)	(3)	(4)	(5)
<b>Mean Equation</b>					
AR (-20)	0.0566 (0.0461)	0.0585 (0.0461)	0.0605 (0.0461)	0.0526 (0.0472)	0.0530 (0.0477)
Constant	0.0004 (0.0007)	0.0004 (0.0007)	0.0003 (0.0007)	0.0004 (0.0007)	0.0004 (0.0007)
<b>Variance Equation</b>					
D1	0.0295 (0.1878)	-0.3094 (0.7804)	-0.2515 (0.7433)	-0.1331 (0.6029)	-0.1349 (0.6056)
D2		0.3666 (0.7681)	-0.0656 (1.1493)	-0.1931 (0.9298)	-0.1862 (0.9305)
D3			0.4186 (0.7872)	0.8930 (0.6439)	0.8898 (0.6426)
D4				-0.7113*** (0.1830)	-0.6635*** (0.2519)
D5					-0.0834 (0.2880)
ARCH (-1)	0.1498*** (0.0274)	0.1521*** (0.0283)	0.1507*** (0.0295)	0.1372*** (0.0247)	0.1400*** (0.0265)
GARCH (-1)	0.7339*** (0.0550)	0.7287*** (0.0564)	0.7182*** (0.0598)	0.6593*** (0.0791)	0.6556*** (0.0796)
Constant	-10.3212*** (0.3041)	-10.2989*** (0.3041)	-10.2391*** (0.3040)	-9.9355*** (0.3171)	-9.9289*** (0.3146)

## 4. Discussion

Compared with the existing literature, this paper does not comprehensively analyze the impact of the Sino-US trade conflict on the global scale [10] but focuses on its impact on the Chinese manufacturing market. The research results show that in the Sino-US trade conflict, the US tariffs on China did not cause fluctuations in manufacturing yields, and the Chinese economy still has a considerable degree of risk resistance in the long run in the face of external shocks. Therefore, the Chinese government does not need to worry about the impact of manufacturing in the trade war, and it will have more options at the strategic level. For investors, the research conclusions of this paper can make them more confident to invest in the manufacturing market, which is helpful for investors' income and choice. Under this research, the resistance of other economic markets in China to external risks and the diversity of risk resistance of the manufacturing market can be studied in the future.

## 5. Conclusion

In order to study whether the Sino-US trade conflict has an impact on China's manufacturing industry, this paper collects the time series of the closing price index of China's manufacturing industry from January 2, 2018, to February 28, 2020, and analyzes its logarithmic rate of return. After confirming the stationarity of the logarithmic return, it determined its ARMA order. Then it introduced dummy variables based on 5 dates when the US imposed tariffs on China during the US-China trade war. After confirming that there is conditional heteroskedasticity in the time series, GARCH Model and ARMA-GARCH Model were used to calculate the data respectively, and the correlation coefficient and significance were obtained. The results show that in the Sino-US trade conflict, the US tariffs on China did not cause fluctuations in manufacturing yields, and the Chinese economy still has a considerable degree of risk resistance in the long run in the face of external shocks. Therefore, the Chinese government does not need to worry about the impact of the Sino-US trade conflict on the manufacturing industry, and will not be passive in terms of diplomacy.

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