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Investigating the Impact of Trade Frictions on China's CSI 300 Index Under the HAR-RV-(C)J-Event Model

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Abstract:
The Sino-US trade friction has garnered significant attention from various sectors. Studying the impact of Sino-US trade friction on China's financial market volatility is of contemporary significance. this study uses the HAR-RV event extension model and the intraday jump Logistic model to quantitatively analyze the effects of Sino-US trade friction events on the CSI 300 Index and industry indices affected by increased tariffs (agricultural products, communication equipment, specialized equipment, medical devices, railway transportation, aerospace equipment). The study finds that Sino-US trade friction events can cause rapid but short-lived impacts on these indices; US sanctions announcements have a greater impact on the Chinese market than Chinese sanctions announcements; the communication equipment and medical device industries are most affected by US sanctions announcements; introducing trade friction events enhances the predictive power of the volatility prediction model both within and outside the sample. The empirical results of this study can serve as a reference for policymakers in preventing systemic financial risks.

Keywords: trade friction, volatility prediction, realized volatility, jump, high frequency data

1. foreword

On March 9, 2018, U.S. President Trump signed a proclamation declaring that imported steel and aluminum products posed a threat to U.S. security, and decided to impose comprehensive tariffs on these imports. This unilateral trade protectionist action by the U.S. violated World Trade Organization rules. As a major exporter, China's interests were severely threatened. From March 2018 to June 2019, Sino-U.S. trade tensions escalated, with the scope and value of the affected products gradually expanding. This not only impacted the import and export businesses of both countries but also affected the stability of the global economy and financial system. In this context, quantifying the economic and financial market impacts of Sino-U.S. trade friction will be a significant topic of long-term academic interest.

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Compared to economic data with long cycles and low frequency, financial market data is characterized by high frequency and large volume. this study focuses on the stock market to analyze the impact of Sino-US trade friction. Currently, most studies use event analysis to measure the impact of macro events on market excess returns, but there is less literature that examines the impact of events on market volatility. Given the critical role of volatility in predicting asset pricing and risk management, quantifying the impact of Sino-US trade friction on market volatility is worth attention. Traditional asset pricing models and arbitrage models can only measure linear risks of assets and cannot account for the discontinuous nature of financial market data, which leads to jump risks (Zhou et al., 2019). Jump risks primarily stem from exogenous major events. Sino-US trade friction is likely to increase market jump risks. Therefore, this study aims to reveal the impact mechanism of Sino-US trade friction on financial markets by quantifying its impact on market volatility across different industries. In terms of model selection

At present, the widely used HAR-RV family model still has limitations in terms of influencing factors and time dimensions. this study attempts to introduce macro event factors into HAR-RV to improve the fitting effect and prediction ability, and to conduct jump detection on the high-frequency data after VMD and wavelet soft threshold denoising, to explore the impact of events on the risk of jumps.

This article is structured into four sections. The first section reviews the relevant literature. The second section introduces the models and methods, including the Volatility Prediction Model (HAR-RV family), Nonlinear Nonstationary Data Denoising Models (VMD and Wavelet Analysis), Intraday Jump Test Methods (L-M Test), and Event Impact Analysis on Intraday Jumps (Logistic Regression). The third section presents empirical results, including data explanations of trade friction events and related index trends, the impact of trade friction events on intraday jumps, and the effect of these events on the in-sample fit accuracy and out-of-sample prediction ability of the volatility prediction model. The fourth section concludes the study with policy recommendations.

2. Research models and methods

2.1 Base Model: HAR-RV (Time-Varying Volatility)

Proposed by Corsi (2009), the model captures volatility's multi-scale nature—short-term (1 day), medium-term (~5 days), and long-term (~22 days)—by using lagged averages of these components to forecast future volatility.

$$\mathrm{RV_t = \beta_0 + \beta_d RV_{t-1} + \beta_w RV_{t-5,t-1} + \beta_m RV_{t-22,t-1} + \epsilon_t}$$

RV_{t-1} : Realized volatility of the previous day (daily volatility).

$RV_{t-5,t-1}$: Average volatility of the first 5 days (weekly volatility).

$RV_{t-22,t-1}$: Average volatility for the first 22 days (monthly volatility).

2.2 First Enhancement: Incorporating Jump Components (Capturing Extreme Shocks) (cj)

Volatility is decomposed into continuous variation (C_t) and discontinuous jumps (J_t), analyzing how past jumps across different horizons influence future volatility.

2.2.1 Background: Market fluctuations are often composed of continuous changes and sudden jumps (such as extreme events).

2.2.2 Decomposition of volatility:

$$RV_t = C_t + J_t$$

C_t : Continuous fluctuations (smooth section).

J_t : Jumping fluctuations (discrete shocks).

2.2.3 Model upgrade(HAR-RV-CJ):

$$\mathrm{RV_t = \beta_0 + \beta_d C_{t-1} + \beta_j J_{t-1} + \beta_w C_{t-5,t-1} + \beta_{wj} J_{t-5,t-1} + \beta_m C_{t-22,t-1} + \beta_{mj} J_{t-22,t-1} + \epsilon_t}$$

Distinguishing between continuous and jump fluctuations on different time scales has implications for the future.

2.3 Extension 2: Add event variables(Event)

2.3.1 Motivation: Events such as macroeconomic announcements, policy changes and corporate earnings may cause abnormal market fluctuations.

2.3.2 Event variable form:

Dummy variables (e.g., event occurrence day = 1, otherwise = 0).

Intensity variables (such as event importance ratings, market sentiment index).

2.3.3 Model upgrade(HAR-RV-(C)J-Event):

$$\mathrm{RV_t = \beta_0 + \sum_{k\in\{d,w,m\}} \left(\beta_k^C C_{t-k} + \beta_k^J J_{t-k}\right) + \gamma \cdot Event_{t-1} + \epsilon_t}$$

Event variables (events) can be lagged over multiple periods or classified by event type (e.g., political events, industry events)。

2.4 Model advantages

2.4.1 Capture complex fluctuation characteristics:

Distinguish between continuous fluctuations and jumps to improve the prediction of extreme risks.
The explanatory power of event variable enhancement model for sudden shock.

2.4.2 Flexibility:

Adjust the time scale (e.g., hours, weeks) or event definition (e.g., social media sentiment).

2.4.3 Empirical performance:

Lower prediction error compared to traditional garch or basic har-rv, especially during a crisis.

2.5 Application scenarios

2.5.1 High-frequency trading: Predict short-term volatility to optimize trading strategies.

2.5.2 Risk management: Evaluate var (value at risk) and es (expected shortfall).

Policy analysis: Quantifying the impact of specific events (such as a Fed rate hike) on markets.

2.6 Noise reduction methods VMD (Variational Mode Decomposition)

VMD is a signal denoising method based on variational mode decomposition (VMD). VMD is an adaptive and fully non-recursive signal decomposition method, which can decompose complex signals into a series of inherent mode functions (IMF) with different central frequencies.

2.6.1 VMD The basic principle of noise reduction

VMD decomposition: the noisy signal is decomposed into k modal components(IMF).
Noise identification: distinguish the noise dominant mode from the signal dominant mode by some criteria (such as correlation coefficient method and energy method).
Signal reconstruction: retain the dominant mode of the signal, discard or weaken the dominant mode of the noise, and realize noise reduction.

2.6.2 VMD Noise reduction steps

(1) parameter setting：
Select the number of modes K
Set penalty parameters α (usually around 2000)
Determine the convergence tolerance τ
(2) Execute VMD decomposition:
Pseudo-code example
u, omega = VMD(signal, alpha=2000, tau=0, K=5, DC=0, init=1, tol=1e-7)
(3) Modal selection:
Calculate the correlation coefficient between each mode and the original signal.
Set the threshold and retain the modes with high correlation.
(4) Signal reconstruction:
denoised_signal = sum(selected_modes)

2.6.3 Suggestions for VMD parameter selection

(1) Mode number k: It is usually determined by observing the spectrum or using optimization algorithms
(2) Punishment parameter α : control the bandwidth, the larger the value, the smaller the bandwidth
(3) Convergence criteria: usually 1e-6 to 1e-7

2.6.4 Advantages of VMD noise reduction

(1) Compared with EMD, AMD avoids the problem of mode mixing.
(2) It has a mathematical theoretical basis and is more stable in decomposition.
(3) It has good effect on non-stationary signal processing.

2.7 Intraday jump test method

The intraday jump test method proposed by Lee and Mykland (2008) is a non-parametric statistical test based on high-frequency data, designed to detect significant jumps (i.e., abrupt and discontinuous price fluctuations) in financial asset prices over extremely short periods. By integrating standardized returns with extreme value theory, this method effectively distinguishes between continuous and discontinuous price movements. The following is a detailed introduction to this method:

2.7.1 Background and core ideas

Jump: In financial markets, asset prices may change dramatically in an instant due to unexpected events (such as news releases, liquidity shocks), and this discontinuous change is called a “jump”.
Research significance: Jumps have an important impact on risk management, option pricing and volatility modeling. Traditional models (such as geometric Brownian motion) assume that prices are continuous and ignore jumps may lead to underestimation of tail risks.
Core idea: calculate local volatility through high-frequency data, standardize the return rate, and use extreme value statistics to identify jumps.

2.7.2 Method steps

Step 1: Data preprocessing
– Divide the trading day into equal intervals (e.g., 5 minutes), and record the price at each moment as, corresponding to the return rate:

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$$r_i = log\left(P_{t_i}\right) - log\left(P_{t_{i-1}}\right)$$

(1) Step 2: Estimate local volatility

The continuous fluctuation component (excluding the influence of jumps) is estimated using the realized bipower variation (bipower variation, bv):

$$\hat{\sigma}_i^2 = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} \left|r_j\right| \cdot \left|r_{j-1}\right|$$

This includes the length of a local window (such as 10 intervals).

(2) Step 3: Standardize the rate of return

Standardize each yield to eliminate the impact of volatility:

$$L_i = \frac{r_i}{\hat{\sigma}_i}$$

(3) Step 4: Construct the test statistic

Calculate extreme value statistics:

$$S = \max_{1 \leqslant i \leqslant n} \left|L_i\right|$$

(4) Step 5: Determine the critical value

According to the extremum theory, when $n \to \infty$, The asymptotic distribution of the statistic S converges to the Gumbel distribution:

$$\text{criticalvalue} = \frac{C_n - log\left(-log\left(1-\alpha\right)\right)}{C_n}$$

among：

$$C_n = \sqrt{2logn} - \frac{log\pi + log\left(logn\right)}{2\sqrt{2logn}}\alpha$$

Significance level (e.g. 5%)

(5) Step 6: Hypothesis testing

If $S > criticalvalue$, The null hypothesis (no jump) is rejected and it is assumed that there is a jump in the corresponding interval.

2.8 Key assumptions

The price process consists of a continuous diffusion part and a finite jump.

The frequency of high-frequency data is high enough to make local volatility estimates reliable.

The jumps are sparse in time (i.e., the number of jumps is finite).

3. Empirical results

3.1 Trade friction event data

According to official announcements, from March 2018 to June 2019, a total of 33 trade friction incidents occurred. Among these, the U.S. imposed trade sanctions on China 20 times, and China retaliated with tariffs 13 times. The U.S. sanctions primarily targeted China's high-tech industries, communication equipment, and key import sectors such as railway transportation, aerospace equipment, and precision instruments. In response, China mainly retaliated against agricultural products and mineral fuels. Therefore, this study focuses on industries significantly affected by relevant tariff clauses, including agricultural products, communication equipment, medical devices, railway transportation, and aerospace equipment. The CSI 300 Index includes representative stocks with strong liquidity and large scale from the Shanghai and Shenzhen stock markets, excluding suspended, ST, or stocks with abnormal operating conditions, severe financial losses, significant price fluctuations, or obvious market manipulation. This study selects the CSI 300 Index to represent the overall market performance.

3.2 Stock Index Market Data

this study obtains 5-minute market data for the CSI 300 Index and six industry indices (classified by Shenwan) from financial databases such as Wind and Tianruan, covering the period from January 1, 2017, to June 27,2019, and conducts statistical analysis. As shown in Table 1□, the return series of all market indices exhibit a 'fat-tailed' distribution, with negative skewness and far higher kurtosis compared to normal distributions. All indices do not conform to a normal distribution. In 2018, all seven indices showed lower returns and higher standard deviations. The 5-minute average return in 2018 was 250% lower than in 2017, and the standard deviation increased by 52% on average compared to 2017. Due to the easing of Sino-US trade negotiations in 2019, the average return for 2019 was positive. However, due to the uncertainty of the negotiation process, the standard deviation of returns in 2019 remained high (up 22% from 2018 and 87% from 2017).

Table 2 lists the descriptive statistics of realized volatility of each market index. Among the industry indexes, the aerospace equipment and communication equipment industry index has the largest volatility, while the special equipment, agricultural products and railway transportation industry index has the smallest volatility.

Table 1 Descriptive statistics of market index returns (CSI 300 Index)

time	mean value	midvalue	Maximal value	Minimum value	Measure of skewness	kurtosis	J-B value	standard deviation
2017	1.66E-05	1.81E-05	1.67E-02	-1.46E-02	-2.18E-01	2.11E+01	1.59E+05	9.77E-04
2018	-2.50E-05	-6.56E-05	2.27E-02	-3.32E-02	-2.04E+00	5.18E+01	1.17E+06	1.77E-03
2019	4.31E-05	2.71E-05	2.42E-02	-3.25E-02	-6.84E-01	3.71E+01	2.72E+05	1.95E-03
total	5.00E-06	-1.23E-05	2.42E-02	-3.32E-02	-1.53E+00	5.57E+01	3.37E+06	1.54E-03

Table 2 Descriptive statistics of realized volatility of market indices (CSI 300 index and agricultural products index)

The CSI 300 index				Agricultural price index			
	RV	RVW	RVm		RV	RV	RV”
Mean value	5.56E-05	5.54E-05	5.44E-05	Mean value	1.78E-04	1.77E-04	1.73E-04
Mid value	3.42E-05	4.18E-05	4.79E-05	Mid value	7.15E-05	7.57E-05	8.99E-05
Maximal value	6.71E-04	2.51E-04	1.57E-04	Maximal value	2.76E-03	1.46E-03	9.64E-04
Minimal value	3.39E-06	6.58E-06	1.00E-05	Minimal value	9.80E-06	1.55E-05	2.20E-05
Measure of skewness	4.47E+00	1.66E+00	8.41E-01	Measure of skewness	3.72E+00	2.49E+00	2.18E+00
kurtosis	3.05E+01	5.78E+00	2.91E+00	kurtosis	2.19E+01	9.46E+00	6.63E+00
J - B value	2.03E+04	4.55E+02	6.89E+01	J-B value	1.00E+04	1.62E+03	7.82E+02
standard deviation	7.18E-05	4.57E-05	3.49E-05	standard deviation	2.89E-04	2.42E-04	2.18E-04

3.3 Analysis of intra-day jump test after VMD and wavelet soft threshold denoising

The yield jumps of the two indices after noise reduction indicate that, the frequency of market jumps in 2018 and 2019 was significantly higher compared to 2017. In 2017, most indices experienced fewer than 10% of the trading days with jumps. However, this ratio increased significantly in 2018 and 2019. In 2018, the average number of trading days with intraday jumps was 50, accounting for 20.6% of the total 243 trading days. In 2019, the average number of trading days with intraday jumps was 19, representing 16.2% of the 117 trading days over six months.

To more accurately examine the impact of various events on intraday jumps in the market the following day, this study uses a logistic model to assess the influence of different types of events on intraday jumps in various market indices. The regression results are presented in Table 3. Only China’s announcement of pressure on the United States and the simultaneous announcements of pressure by both China and the United States had an impact on intraday jumps the following day. The study found that different indices were affected differently by news. The probability of intraday jumps for the communication equipment and medical devices sectors was significantly influenced by the U.S. announcement; the probability of intraday jumps for the SSE 300 Index and railway transportation was significantly influenced by the simultaneous announcements from China and the United States. Notably, on April 16,2018, the U.S. imposed sanctions on ZTE Corporation, but the telecommunications industry did not show a significant market reaction after the incident. The reason was that ZTE announced a suspension from trading until June 13, and its market value was 85.74 billion yuan, accounting for 12% of the total market value of the index components, making it a key stock in the sector. Therefore, the impact on the industry index from April 16 to 21 was minimal. After resuming trading on June 13, ZTE experienced consecutive daily limits down until June 25, and the telecommunications industry detected intraday jumps on June 15.

The empirical results indicate that the U.S. sanctions announcement increases market volatility, but this result should be viewed with a rational perspective. The U.S. sanctions primarily target the export of technology products to the United States. Since 5G is one of the few emerging technologies capable of competing with European and American intellectual property, communication

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equipment is most vulnerable to U.S. sanctions. However, a series of U.S. measures aimed at blocking Chinese communications have proven ineffective, demonstrating the maturity of China's communication industry. The U.S. aims to replicate its previous suppression strategy against Japan in this trade war, not only by imposing technological restrictions on Chinese communication companies like Huawei but also by collaborating with European countries to join the blockade. Ultimately, the market will make a rational choice; many European countries do not support U.S. bans, and countries such as Spain, the UK, and Switzerland have already begun using Huawei technology to launch 5G networks in some cities.

Table 3 Logistic regression results of trade friction events and market index jumps

	HS300	farm produce	farm produce	dedicated device	medical apparatus and instruments	railway transportation	Space equipment
θA	-0.0386 (-0.15)	0.685 (1.12)	1.176" (2.10)	-0.306 (-0.39)	1.397" (2.39)	-0.642 (-0.61)	0.164 (0.25)
θc	-0.193 (-0.04)	1.091 (1.46)	0.365 (0.44)	0.387 (0.47)			0.953 (1.28)
θg	2.446" (1.98)		0.77 (0.62)	0.793 (0.64)	1.292 (1.04)	2.616" (2.11)	0.77 (0.62)
α	-1.753 (-10.74)	-1.601" (-10.33)	-1.464** (-9.87)	-1.486 (-9.95)	-1.985* (-11.17)	-1.923" (-11.07)	-1.464** (-9.87)

Note: The t-statistic is in parentheses; ***, ** and * indicate significance at the level of 1%,5% and 10%, respectively

3.4 In-sample estimation and out-of-sample prediction of har-rv family models

this study introduces the publication date of trade frictions as an external event factor into the har-j and har-rv-cj models, constructing two new models: har-j-event and har-rv-cj-event. To fully reflect the impact of market volatility on predictions at different lags, this study selects three prediction intervals (h=1,2,5,10) to estimate the models, analyzing how historical volatility characteristics affect the average market volatility over 1 day, 2 days, 1 week, and 2 weeks. Table 4 presents the sample-based estimation results of the CSI 300 Index overall sample data in various volatility models. To eliminate the influence of the number of explanatory variables on model fitting, this study uses the adjusted r² as the evaluation metric for fitting performance.

Given the similar parameter estimation results of various index volatility models within the sample, this study uses the sample-based estimation results of the CSI 300 Index as an example □. As shown in Table 4, βa and β are mostly significant at the 5% level, indicating that current volatility is influenced by the superposition of daily and weekly volatility. This phenomenon aligns with Muller's (1997) heterogeneous market hypothesis, confirming the existence of heterogeneity among stock market traders in China. The behavior of investors varies across different cycles and holding periods. As the prediction window extends, the coefficients of βa, β, and βm gradually decrease, suggesting that the impact of current volatility on future volatility diminishes as the prediction window lengthens. be is significantly positive at t=1 and becomes insignificant when the prediction window exceeds one day, indicating that events only affect the volatility of the next trading day. Therefore, this study focuses on analyzing the impact of events on the volatility of other industry indices when the prediction period is one day (t=1). The empirical results of the har-rv family model are presented in Table 5. The volatility of most indices is impacted by trade friction events, with only U.S.-issued trade sanctions showing a significant response. In conjunction with the analysis of the impact of events on intraday jumps, it is evident that the impact of events on the market is rapid and short-lived, consistent with the findings of li (2019) and ramia et al. (2016). By comparing the adjusted r² of each model, it is evident that introducing jump variables and event variables in the har-rv model enhances its fitting performance. This suggests that macro events provide new information, which can enhance the model's predictive power. This finding further supports the views of maetal. (2019), zhouetal. (2019), and arourietal. (2019), indicating that market short-term volatility is easily influenced by significant events. The paper speculates that trade frictions increase market volatility due to their high visibility, which triggers short-term changes in investor sentiment and, consequently, affects short-term market volatility. The study uses a rolling window out-of-sample regression method to compare the out-of-sample performance of six har-rv models. Given that the first trade friction event occurred in March 2018, the study uses the period from March 1 to December 21,2018, as the initial sample regression interval, with dynamic predictions based on the sample data from the 200 trading days prior to day.

Table 4 Parameter estimation results of various volatility models in CSI 300 sample

					H=1						
	β_d	β_w	β_m	β_j	β_{j-W}	β_{j-m}	β_{event}	β_{eventA}	β_{eventC}	β_{eventC}	R²
HAR-RV	0.00793 (0.16)	0.549** (5.59)	0.128 (1.17)								0.164
HAR-RV-J	0.362. (3.76)	0.463. (4.69)	0.0962 (-0.89)	-0.625” (-4.29)							0.188
HAR-RV-J-Event	0.357” (3.73)	0.469** (4.77)	0.0661 (0.61)	-0.632* (-4.36)			7.43E- 05” (2.53)				0.195
HAR-RV-J-Event-D	0.356* (3.71)	0.465** (4.73)	0.0741 (0.69)	-0.619.* (-4.25)				9.93E- 05’ (2.60)	1.05E- 04 (1.4)	-7.47E- 06 (-0.14)	0.195
HAR-RV-CJ	0.224” (2.28)	0.687. (3.69)	0.155 (0.72)	-0.163 (-1.95)	0.23 (1.1)	-0.138 (-0.39)					0.190
HAR-RV-CJ-Event	0.224” (2.29)	0.658* (3.55)	0.169 (0.79)	-0.179” (-2.14)	0.279 (1.34)	-0.239 (-0.67)	7.31 E-05” (2.48)				0.196
HAR-RV-CJ-Event-D	0.222” (2.27)	0.665. (3.58)	0.162 (0.76)	-0.166” (-1.97)	0.261 (1.25)	-0.208 (-0.58)		9.95E- 05” (2.60)	9.92E- 05 (1.32)	-1.04E- 05 (-0.19)	0.196
					H=2						
HAR-RV	0.0668’ (2.44)	0.244*” (4.58)	0.205* (3.48)								0.2511
HAR-RV-J	0.322** (6.27)	0.184* (3.49)	0.181” (3.17)	-0.457. (-5.82)							0.292
HAR-RV-J-Event	0.322** (6.26)	0.185* (3.49)	0.179” (3.1)	-0.458” (-5.82)			5.56E- 06 (0.35)				0.291
HAR-RV-J-Event-D	0.320*” (6.22)	0.186* (3.51)	0.179” (3.1)	-0.450* (-5.70)				1.73E- 05 (0.87)	3.92E- 05 (0.98)	-3.54 E-05 (-1.23)	0.292
HAR-RV-CJ	0.182” (2.82)	0.696.* (5.69)	0.107 (0.76)								0.28
HAR-RV-CJ-Event	0.185° (2.5)	0.707. (5.05)	0.118 (0.73)	-0.0906 (-1.44)	0.149 (0.95)	-0.117 (-0.43)	2.7E-05 (1.22)				0.281
HAR-RV-CJ-Event-D	0.185’ (2.5)	0.717… (5.11)	0.105 (0.65)	-0.0826 (-1.30)	0.135 (0.85)	-0.0982 (-0.36)		4.25E- 05 (1.52)	3.09E- 05 (0.55)	-2.25E- 05 (-0.55)	0.28

The empirical findings of this study are similar to other studies on the financial impact of major international events. The Sino-US trade friction, a global concern, significantly affects investor sentiment, increasing market uncertainty and causing short-term increases in market volatility and more frequent intraday jumps. This event

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has a brief impact, affecting only the next trading day. According to the results of har-rv-c-j-event-d, most industries affected by tariffs show the most significant next-day volatility due to the US sanctions, but the intraday jump risks vary across different industries, with communication equipment and medical devices being the most affected. Although communication equipment, medical devices, and aerospace equipment are all key sectors targeted by the US for high-tech industries from China, their impacts differ due to varying levels of development. Communication equipment is the most severely impacted by US sanctions. In April 2018, the US imposed an 892 million yuan fine on ZTE (the largest fine in US history for violating export control); from December 2018 to June 2019, the US continued to impose sanctions on Huawei, significantly impacting the telecommunications industry's stock prices. However, due to European countries not supporting the US ban and US suppliers expressing dissatisfaction with the US government's policies, the US trade sanctions on China's telecommunications market will not continue, and the long-term negative impact will not be profound. China's medical device export industry mainly relies on low-end products and is less mature compared to the telecommunications sector. Sanctions on medical devices by the United States will cause low-end products in the industry to lose competitiveness due to price hikes, and the development of high-end products will be hindered. In the aerospace sector, China's cooperation with the United States exceeds competition. China provides a vast market for U.S. civilian aviation products and supplies aviation components and upstream materials to American companies. Since 2012, China has been the top exporter of U.S. civil aircraft, aviation engines, and parts for six consecutive years, with exports exceeding $16.2 billion in 2017. Additionally, China is also an importer of U.S. aerospace vehicles. In 2017, the trade surplus between the United States and China in aerospace vehicles and parts reached $15.8 billion. In the long term, Trump's trade sanctions will ultimately harm U.S. domestic enterprises, and it is expected that these policies will not last.

Table 5 Parameter estimation results of the volatility model of each industry index within the sample (h=1) farm produce

	β_d	β_w	β_m	β_j	β_{j-W}	β_{j-m}	β_{event}	β_{eventA}	β_{eventC}	β_{eventC}	R²
HAR-RV	0.130" (2.55)	0.596** (6.47)	0.181" (2.24)								0.537
HAR-RV-J	0.430.* (6.11)	0.403. (4.24)	0.200" (2.54)	-0.572* (-5.99)							0.561
HAR-RV-J-Event	0.433" (6.17)	0.401. (4.23)	0.193' (2.47)	-0.574* (-6.03)			7.82E-05" (2.11)				0.564
HAR-RV-J-Event-D	0.436" (6.19)	0.399** (4.21)	0.193" (2.40)	-0.577. (-6.04)				8.1E-05° (1.65)	4.8E-06 (0.05)	7.77E-05 (1.2)	0.562
HAR-RV-CJ	0.415. (5.58)	0.372" (3.17)	0.251" (2.41)	-0.128° (-1.76)	0.484" (2.66)	-0.00769 (-0.03)					0.559
HAR-RV-CJ-Event	0.424*** (5.71)	0.360*.* (3.08)	0.232" (2.22)	-0.134' (-1.85)	0.500.* (2.76)	0.0455 (0.16)	7.81E-05" (2.07)				0.561
HAR-RV-CJ-Event-D	0.427"* (5.73)	0.358*** (3.05)	0.232" (2.21)	-0.134 (-1.85)	0.498" (2.74)	0.0437 (0.16)		8.22E-05 (1.67)	6.98E-06 (0.07)	7.3E-05 (1.12)	0.56

Table 6 Results of hmse test on samples inside and outside the har family model of market index Within the sample

	The CSI 300 index	Farm produce	Communication apparatus	Communication apparatus	Medical apparatus and instruments	Railway transportation	Space equipment
HAR-RV	1.7445	1.6606	2.1817	2.2156	1.3963	0.8724	1.7054
HAR-RV-J	1.4176	1.4782	2.0981	2.0995	1.2987	0.8345	1.7008
HAR-RV-E	1.3828	1.4347	2.0229	2.1045	1.3088	0.8383	1.6389
HAR-RV-E-D	1.3931	1.4477	2.0068	2.1326	1.3213	0.8545	1.6368
HAR-RV-CJ	1.2561	1.4641	1.9316	1.8997	1.2141	0.8142	1.6923
HAR-RV-CJ-E	1.2230	1.4239	1.8366	1.8948	1.2255	0.8205	1.6299
HAR-RV-CJ-E-D	1.2388	1.4378	1.8351	1.9234	1.2410	0.8349	1.6278

Table 7 Outside the sample

	The CSI 300 index	Farm produce	Communication apparatus	Communication apparatus	Medical apparatus and instruments	Railway transportation	Space equipment
HAR-RV	1.0912	0.5491	0.6075	1.1903	1.2815	0.6851	0.6851
HAR-RV-J	1.1059	0.5240	0.6052	1.1864	1.1855	0.6734	0.6734
HAR-RV-E	1.0715	0.5196	0.5817	1.1454	1.1542	0.6517	0.6517
HAR-RV-E-D	1.0641	0.5067	0.5687	1.1444	1.1320	0.6395	0.6395
HAR-RV-CJ	1.1087	0.3672	0.5851	1.7710	1.5259	1.0319	1.0319
HAR-RV-CJ-E	1.2911	0.3692	0.6036	1.9751	1.4209	1.0456	1.0456
HAR-RV-CJ-E-D	1.3506	0.3746	0.6092	2.0352	1.4525	1.0445	1.0445

The empirical findings of this study are similar to other studies on the financial impact of major international events. The Sino-US trade friction, a global concern, significantly affects investor sentiment, increasing market uncertainty and causing short-term increases in market volatility and more frequent intraday jumps. This event has a brief impact, affecting only the next trading day. According to the results of har-rv-c-j-event-d, most industries affected by tariffs show the most significant next-day volatility due to the US sanctions, but the intraday jump risks vary across different industries, with communication equipment and medical devices being the most affected. Although communication equipment, medical devices, and aerospace equipment are all key sectors targeted by the US for high-tech industries from China, their impacts differ due to varying levels of development. Communication equipment is the most severely impacted by US sanctions. In April 2018, the US imposed an 892 million yuan fine on ZTE (the largest fine in US history for violating export control); from December 2018 to June 2019, the US continued to impose sanctions on Huawei, significantly impacting the telecommunications industry's stock prices. However, due to European countries' opposition to the US ban and dissatisfaction among US suppliers with the government's policies, the US trade sanctions on China's telecommunications market will not continue, and the long-term negative impact will not be profound. China's medical device export industry mainly relies on low-end products and is less mature compared to the telecommunications sector. Sanctions on medical devices by the United States will cause low-end products in the industry to lose competitiveness due to price hikes, and the development of high-end products will be hindered. In the aerospace sector, China's cooperation with the United States exceeds competition. China provides a vast market for U.S. civilian aviation products and supplies aviation components and upstream materials to American companies. Since 2012, China has been the top exporter of U.S. civil aircraft, aviation engines, and parts for six consecutive years, with exports exceeding $16.2 billion in 2017. Additionally,

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China is also a major importer of U.S. aerospace vehicles. In 2017, the trade surplus between the United States and China in the aerospace sector reached $15.8 billion. In the long term, Trump's trade sanctions will ultimately harm U.S. domestic enterprises, and it is expected that these policies will not last long.

References

[1] Wang Rutong, Li Wenqi, and Huang Yirong. Trade Frictions, Intraday Volatility, and Stock Market Fluctuations —— Empirical Evidence Based on China's High-Frequency Data [j]. International Finance Research, 2019,(12):63-73.doi:10.16475/j.cnki.1006-1029.2019.12.007.

[2] Qiaoting and Lin Qiaolong. The Reform of the Registration System and Stock Market Volatility —— Evidence from the Growth Enterprise Market [j]. Securities Market Guide, 2024,(01):64-79.

[3] Dai T. Reform of the trading system of the Growth Enterprise Market [d]. Shanghai University of Finance and Economics, 2021.doi:10.27296/d.cnki.gshcu.2021.002192.

[4] Lu Hengtian and Yao Hengyu. Simulation Study on the Impact of Changes in Price Limit Fluctuations on Market Volatility and Liquidity [j]. Systems Engineering Theory and Practice, 2022,42(04):897-905.

[5] Liu Hailong, Wu Wenfeng, and Wu Chongqiang. The Impact of Price Limit on Stock Market Volatility [j]. Journal of Shanghai Jiao Tong University, 2005,(10):1569-1573.doi:10.16183/j.cnki.jsjtu.2005.10.001.

[6] Liu Yang. Analysis on the Impact of Trading Mechanism on Volatility of China's Securities Market [j]. Nankai Economic Research, 2003, (04):65-70.

[7] Wen Mei. Cross-market volatility analysis based on computational experimental methods [d]. Tianjin University, 2010.

[8] Li Tao, Tu Wei, Li Bing, et al. Tariff shock and enterprise digital technology application [j]. Economic Research, 2024,59(12):130-148.

[9] Zhu Tianming. The Impact of Sino-US Trade Frictions on Stock Market Liquidity —— Based on Evidence from the A-share Market [j]. Zhejiang Finance, 2024, (07):70-80.

[10] Xue Jing. The Impact of Sino-US Trade Frictions on the Performance of Chinese Enterprises [d]. Southwestern University of Finance and Economics, 2024.