Research On the Impact of China's Industrial Chain Security Under US-China Trade Friction Based on DID Methodology

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Abstract. This paper mainly studies the security of China's industrial chain under Sino-US trade friction. First, by considering the integrity, stability and competitiveness of the industrial chain, a comprehensive security level measurement system is established. Secondly, through the regression analysis based on the difference in differences model, it is found that the US restrictive policy on China has a negative impact on the security of China's industrial chain, but the measures taken by China to expand multilateral trade, increase exports and promote independent innovation have effectively mitigated the impact. Finally, the robustness test confirms the reliability of the conclusions, and the heterogeneity analysis of 21 industries shows that trade frictions mainly have a negative impact on capital - and technology-intensive industries, especially technology-intensive industries. Based on the conclusions of the model, this paper suggests that we should continue to improve China's industrial chain security monitoring and early warning system, while strengthening policy support for technology-intensive industries to cope with the challenges of international trade uncertainties.

Keywords: Sino-US relations; industrial chain security; entropy weight method; DID.

1. Introduction

Against the backdrop of an intensifying global anti-globalization trend, China-Us trade frictions continue to escalate, posing serious challenges to the security of the global industrial chain. In this regard, a scientific, accurate and comprehensive measurement of industrial chain security is needed to formulate more targeted industrial and trade policies. This paper aims to study the security of China's industrial chain, build a comprehensive measurement system, quantitatively describe the security level of China's industrial chain, and take Sino-US trade friction as an example to quantitatively analyze its impact on China's industrial chain.

Based on the analysis of node security, network structure characteristics [1] and dynamic capability evolution [2] of the industrial chain, this paper discusses the multi-dimensional measurement method of industrial chain security. The existing research mainly focus on a single dimension or a specific industrial chain, which is lack of systematization and comprehensiveness. For the establishment of measurement models, the existing research methods mainly include vertical specialization index [3], export complexity [4] and GVC index [5]. Most of the studies on trade conflict focus on trade benefits and bilateral trade volume and pay less attention to its impact on the industrial chain. Therefore, based on existing literature, this paper will quantitatively analyze the impact of Sino-US trade friction on China from the perspective of industrial chain security, and put forward corresponding suggestions.

2. Empirical Design

2.1. Data Sources

This paper selects the national and world import and export industry data from 2010-2022 to carry out empirical analysis.

Data sources include China Statistical Yearbook, China Input-Output Table (China Input-Output Society), OECD World Input-Output Table, UN Comtrade, General Administration of Customs of

China, etc. Among them, some data have missing years due to official statistical reasons, this paper adopts linear interpolation method to merge to fill the data gaps.

2.2. Model Setting

The difference in differences model [6-7] has been widely used in the empirical research of foreign import and export trade and related industrial chain analysis. This paper adopts the difference in differences method (DID) to analyze the specific impact of Sino-US trade friction on the security of China's industrial chain. By comparing the changes of the treatment group affected by the policy and the control group not affected before and after the implementation of the policy, the method can control the individual fixed effect and the time fixed effect that do not change with time, so as to effectively avoid the endogeneity problem. To sum up, this paper intends to establish the following model:

$$Sec_{it} = \beta_0 + \beta_1 Policy_{it} + \beta_2 Exp_{it} + \beta_3 Policy_{it} Exp_{it} + \gamma D(X) + \omega_{it} + \lambda_{it} + \varepsilon_{it} \tag{1}$$

i represents 21 different industry categories under HS code (Section 1-21), and t represents year (2010-2022).

Where, Sec_{it} is the explained variable, $Policy_{it}, Exp_{it}$ and the cross-multiplying term with it is the explanatory variable. X is the control variable, including ex_t and $texp_{it}$. β_0 represents the model intercept term, $\beta_1, \beta_2, \beta_3$ is the explanatory variable coefficient, γD is the control variable coefficient. ω_{it} represents the individual fixed effect that does not change with time, λ_{it} is the time fixed effect, ε_{it} is the random disturbance term.

In the DID model established in this paper, the cross-multiplication term $Policy_{it} \times Exp_{it}$ is the core explanatory variable of this paper, and the coefficient β_3 represents the impact of Sino-US trade friction on the security of China's industrial chain, and the positive or negative value and magnitude of the value reflect the direction and degree of the impact

2.3. Variable Selection

2.3.1 Explained variable

The Sec_{it} explained variable is the industrial chain security factor constructed in this paper, which is used to measure the security degree of China's industrial chain. This paper mainly defines the security level of China's industrial chain from three dimensions of industrial chain integrity, stability and competitiveness. Under the three dimensions, the domestic self-sufficiency rate of intermediate inputs (SSR), import concentration (HHI) and trade competitiveness (TC) are selected respectively, and the weight of each index is calculated by entropy weight method, and the security coefficient of China's industrial chain is weighted from 2010 to 2022.

$$Sec_{it} = w_1 HHI_{it} + w_2 SSR_{it} + w_3 TC_{it} \tag{2}$$

（1）Integrity of industrial chain

The integrity of the industrial chain refers to the consistency and reliability of all links in an industrial chain system. The domestic self-sufficiency rate of intermediate goods reflects the degree of self-sufficiency of intermediate products required by a country or region in the industrial chain and can reflect the completeness of the industrial chain of a country or region. Its calculation method is as follows:

$$SSR = \frac{GO - TFU}{TIU} \tag{3}$$

Where, GO represents total national output, TFU represents total final use, and TIU represents total intermediate use. The higher the domestic self-sufficiency rate, the lower the dependence on foreign producers and the smaller the risk in the industrial chain.

（2）Industrial chain stability

Industrial chain stability refers to the ability of an industrial chain system to maintain stability and reliability in the face of various internal and external changes and shocks. Import market concentration, also known as the Herfindahl-Hirschman Index (HHI index), measures the concentration of a country or region's import sources for a specific intermediate or raw material. The index is calculated based on the market share or occupation of each participant.

$$HHI = \sum_{i=1}^{n} S_i^2 \tag{4}$$

$$S_i = \frac{Import\ from\ i}{Total\ Import} \tag{5}$$

Where, S_i is the proportion of Country i's industry-wide imports from China to China's industry-wide imports. The higher the HHI, the more concentrated the imports, the lower the diversification, and the greater the risk of the industrial chain.

（3）Industrial chain competitiveness

Industrial chain competitiveness refers to the ability of an industrial chain system to gain competitive advantages in the world market compared with other industrial chain systems, mainly focusing on indicators such as domestic and foreign market share and value-added ability of the industrial chain. This paper reflects the competitiveness of China's industrial chain through the Trade competitiveness index (TC). The calculation method is as follows:

$$TC = \frac{Export\ value - import\ value}{Export\ value + import\ value} \tag{6}$$

The value range of TC is [0,1]. The value near 0 indicates that the competitiveness is average, and the closer to 1 indicates that the international market competitiveness is stronger, and the industrial chain risk is smaller.

2.3.2 Explanatory variables

（1）Policy variables:$Policy_{it}$

Explanatory variables $Policy_{it}$ are dummy variables of whether industry i was affected by Sino-US trade friction in year t, and the classification standard is whether the industry was imposed tariffs in that year.

$$\begin{cases} Tariffs\ imposed\ during\ the\ year:\ Policy_{it} = 1 \\ No\ tariffs\ were\ imposed\ during\ the\ year:\ Policy_{it} = 0 \end{cases} \tag{7}$$

One of the most important manifestations of the Sino-US trade war is the significant increase in tariffs. The increase of tariff barriers directly affects the prices of imported commodities and consumers' purchase intentions, and then affects the security level of China's industrial chain. It is an important index with research value and reference significance.

（2）Annual trade volume by industry:Exp_{it}

Since the research object of this paper is the whole industrial chain, rather than focusing on a single industry, choosing the total amount of export products as a part of the explained variable can more effectively quantify the scope and scale of imports and exports affected by the Sino-US trade war.

（3）Interactive items: $Policy_{it} \times Exp_{it}$

Considering the research Angle of data availability and industrial chain, as well as the specific situation of four rounds of tariffs imposed in the Sino-US trade war, this paper chooses $Policy_{it} \times Exp_{it}$ as the core explanatory variable of the model to establish the DID model.

2.3.3 Control variables

During the research process, a single explanatory variable is likely to lead to missing variable bias, which has a significant impact on the empirical results. Specifically, in addition to Sino-US trade frictions, a country's economic development status, trade environment and foreign trade volume may affect the security degree of the country's industrial chain and bilateral trade volume at the same time. Therefore, from a macro perspective, this paper will introduce the Exchange and China's annual Total export value total-EXP as control variables, representing China's economic development and foreign trade status, in order to solve the possible endogenous problems. In addition, this paper controls the fixed effects of time and individuals, and further controls the missing variables of individuals changing with time and industry.

3. Analysis of Empirical Results

3.1. Construction of Safety Factor of Industrial Chain

3.1.1 Data standardization

In order to eliminate the differences in dimensions and units of each index, this paper adopts the range method to standardize the domestic self-sufficiency rate (SSR), import concentration (HHI) and trade competitiveness (TC) of intermediate products. The entropy method requires different treatment methods for the positive and negative indicators. The formula is as follows:

$$\begin{cases} Y_{ij} = \frac{X_{ij}-min(X_{ij})}{max(X_{ij})-min(X_{ij})} (Positive\ indicator) \\ Y_{ij} = \frac{max\ (X_{ij})-X_{ij}}{max(X_{ij})-min(X_{ij})} (negative\ indicator) \end{cases} \tag{8}$$

Where, X_{ij} represents the value before the processing of the i sample of the j item indicator, and Y_{ij} represents the value after the processing of the i sample of the j item indicator.

3.1.2 Calculate the information entropy value e based on the p-value

Information entropy is essentially the expected value of the amount of information [8]. The greater the probability of an event, the smaller the amount of information. The smaller the probability, the greater the amount of information. It is calculated as follows:

$$E_j = -(\ln \mathrm{n})^{-1} \sum_{\mathrm{i=1}}^{\mathrm{n}} P_{ij} \ln(P_{ij}) \tag{9}$$

Where, P_{ij} is the proportion of the i sample value of the j index, calculated as follows:

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \tag{10}$$

Finally, the information entropy value e is obtained, as shown in Table 1:

Table 1. Information entropy of each index of the safety factor of the industrial chain

	Domestic self-sufficiency rate of intermediate products (SSR)	Concentration of imports (HHI)	Trade competitiveness (TC)
E_j	0.906	0.943	0.908

3.1.3 Calculate weights and scores based on information entropy

According to the E_j calculation of the weight of three indicators, the formula is as follows:

$$W_j = \frac{1-E_j}{\mathrm{n}-\sum_{\mathrm{j=1}}^{\mathrm{n}} Ej} \tag{11}$$

Table 2. Weights of each index of the safety factor of the industrial chain

	Domestic self-sufficiency rate of intermediate products (SSR)	Concentration of imports (HHI)	Trade competitiveness (TC)
W_j	38.55%	23.61%	37.84%

According to the weights shown in Table 2, the safety coefficient of China's industrial chain for 2010-2022 is calculated, as shown in Fig.1.

As can be seen from Figure 1, the safety factor of China's industrial chain continued to rise from 2010 to 2022, showing a long-term strengthening trend. However, it temporarily declined between

2015 and 2018, mainly due to the impact of the Sino-US trade war, which caused damage to export-oriented industries. In 2019, through proactive government measures such as expanding markets, upgrading industries and innovating technologies, the safety factor of the industrial chain was able to recover growth, improving long-term competitiveness and resilience to risks.

3.1.4 The correlation degree of indicators is tested

In this paper, the safety factor of the industrial chain is taken as the parent sequence, and the standardized domestic self-sufficiency rate of intermediate products (SSR), import concentration (HHI) and trade competitiveness (TC) are taken as the sub-sequence, and the grey measure method is used to test whether the composition of the three first-level indicators of the explained variables is reasonable. The test results are shown in Table 3:

Table 3. Correlation degree test of grey prediction indicators

Evaluation items	Relevance	Ranking
TC	0.82	1
HII	0.608	2
SSR	0.599	3

It can be seen from Table 3 that the correlation degree between SSR, HHI and TC and the safety coefficient of the industrial chain is greater than 0.5, indicating that the index selection and composition of the safety coefficient of the industrial chain of the explained variables are reasonable and have a certain representative degree of the safety degree of China's industrial chain.

3.2. Benchmark Regression

According to the results of the Hausmann test, the statistics of all four columns of regression are greater than the critical value at the 1% significance level, rejecting the null hypothesis that there is no significant difference in the estimates of the fixed and random effects models. Therefore, this paper constructs the following fixed effects model for regression.

$$Y_{it} = \beta_0 + \beta_1 Policy_{it} + \beta_2 Exp_{it} + \beta_3 Policy_{it} Exp_{it} + \gamma D(X) + \omega_{it} + \lambda_{it} + \varepsilon_{it} \tag{12}$$

The benchmark regression results are shown in Table 4. The coefficients of the core explanatory variables (cross-multiplication terms) in this paper all passed the significance test at the level of 1%, and the four models could all explain more than 50% of the changes of the total indicators, and the goodness of fit of the regression model was good. Therefore, the model finally constructed in this paper can describe the causal relationship among variables more accurately at the statistical level.

Table 4. Baseline regression results

	(1)	(2)	(3)	(4)
	score	hhi	ssr	tc
Policy	38.76 * * *	0.186 * * *	0.0032	0.912 * * *
	(4.52)	(4.63)	(-0.04)	(4.44)
Lnexp	1.835	0.0492 * * *	0.0308	0.059
	(0.72)	(4.12)	(-1.62)	(0.97)
C.Lnexp#C.Policy	1.358 * * *	0.00772 * * *	0.000297	0.0310 * * *
	(3.62)	(4.39)	(0.09)	(3.44)
Ex	1.695	0.00883	0.00916	0.0278
	(0.58)	(0.65)	(0.35)	(0.4)
Lntexp	5.638 * *	0.0477 * * *	0.0352 *	0.158 * * *
	(2.93)	(5.29)	(2.17)	(3.43)
_Cons	141.8 * *	0.0137	0.984 * *	5.056 * * *
	(2.98)	(0.06)	(3.27)	(4.43)
Hausman	33.08 * * *	18.11 * * *	6.05 * * *	40.07 * * *
R^2	0.64	0.59	0.52	0.63
N	273	273	273	273

Note: ***, **, and * are significant at the 0.1%, 1%, and 5% levels, respectively.

According to the regression results, it can be seen that the policy of trade friction has a significant negative impact on the security of China's industrial chain, and the US trade restrictive measures against China (such as the imposition of tariffs) have greatly weakened the stability of China's industrial chain. However, the annual trade volume of various industries has a positive impact on the security factor of China's industrial chain. The reduction of trade volume will hit the security of China's industrial chain, while the recovery of export volume after 2019 will help to enhance the security of China's industrial chain. The cross-multiplication coefficient is positive, and for each unit increase, the security coefficient of the industrial chain will increase by 1.358 units. It can be seen that despite the challenges brought by Sino-US trade policies, China's countermeasures have offset the adverse effects of Sino-US trade frictions to a certain extent by increasing export volume, diversifying transactions, promoting innovation and other operations, thus protecting the security of the industrial chain.

4. Robustness Test

4.1. Parallel Trend Test

In order to prove that the effect coefficients of the control group and the experimental group have the same change trend before and after the year when the US issued the tariff policy against China, that is, the DID model satisfies the parallel trend hypothesis, the following parallel trend tests are carried out in this paper.

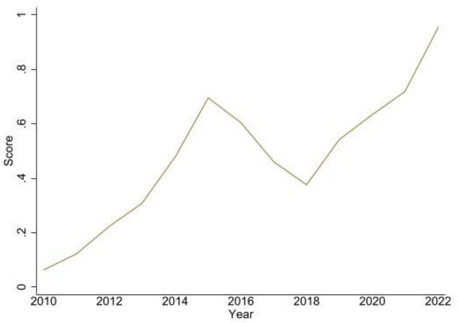

Fig. 1 The change trend of China's industrial chain security coefficient from 2010 to 2022

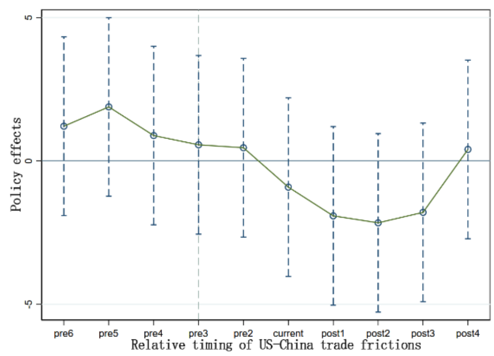

Fig. 2 Results of the parallel trend test

As shown in Fig.2, before the policy occurred, the safety factor of the industrial chain was not seriously affected by the tariff policy. Therefore, the trend of the change of the safety degree of China's industrial chain before and after the implementation of the tariff policy should be different. Before the imposition of tariffs by the United States on China, the confidence intervals of the coefficients all contain 0, indicating that the independent variable before the implementation of the policy has no significant impact on the dependent variable. After the occurrence of the policy, the decreasing trend of the coefficient is obvious, indicating that the policy implementation has a significant effect on the dependent variable, and the different-difference model in this paper satisfies the parallel trend hypothesis.

4.2. Placebo Test

Missing variables in a benchmark model can lead to significant biases and inaccuracies in its estimates and may even lead to false inferences of causality. Therefore, this paper uses random substitution method to perform placebo test on the basis of baseline regression to eliminate the influence of subjective bias and expectation effect [9].

Based on the baseline regression model, 500 random change interaction term regression analyses were conducted in this paper to determine whether the coefficient is significantly different from the baseline estimate results. Fig.3 shows the results of the placebo test.

As can be seen from the test results, the p value of the bilateral test of coefficients is 0.0000, indicating significant differences. Moreover, the image shows that most of the coefficients derived from sampling regression are not significant. Therefore, the result is in line with the expectation of the placebo test, and the interference of potential bias and external factors on the research results of the DID model in this paper can be excluded. Therefore, the research significance and reference value of the core conclusions of this paper can be verified.

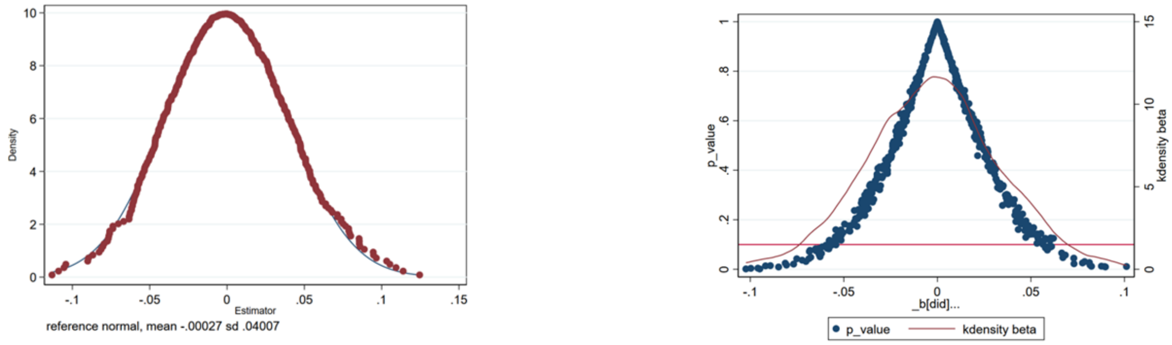

Fig. 3 Distribution of placebo test results

4.3. Hysteresis Effect

The lag effect test considers the time delay relationship between the explanatory variable and the explained variable, which makes the model closer to the actual economic operation. At the same time, it can help better understand the long-term impact of economic policies or external shocks on economic variables, and help formulate more effective policies, which has strong practical significance. The regression test model adopted in this paper is as follows:

$$Y_{it} = \beta_0 + \beta_1 Policy_{it} + \beta_2 Exp_{it} + \beta_3 Policy_{i,t-1} Exp_{i,t-1} + \gamma D(X) + \omega_{it} + \lambda_{it} + \varepsilon_{it} \tag{13}$$

As can be seen from the regression results in Table 5, at the level of the safety factor of the industrial chain, the coefficients of the variables policy, lnexp and cross-multiplication terms are all very significant and pass the hysteresis effect test. In addition, the release of tariff restriction policy has a significant hindering effect on the safety factor of China's industrial chain, and the trade volume of various industries has a significant promoting effect on the safety factor of China's industrial chain.

Specifically, in terms of whether the US imposes tariffs on China, Sino-US trade friction has a significant negative correlation with import concentration (HHI) and trade competitiveness (TC), indicating that the two variables have a strong limiting effect, which seriously affects China's position and competitiveness in the international market and the security degree of the industrial chain. However, the variable coefficient of domestic self-sufficiency rate (SSR) for intermediate inputs is not significant, indicating that the influence on domestic self-sufficiency of China's intermediate inputs is weak, and China will not significantly reduce the production and supply of domestic intermediate products under Sino-US trade frictions.

Table 5. Regression results of hysteresis effect

	(1)	(2)	(3)	(4)
	score	hhi	ssr	tc
Policy	43.65 * * *	0.190 * * *	0.000784	1.034 * * *
	(5.58)	(4.62)	(0.01)	(5.13)
Lnexp	0.035 * * *	0.0437 * * *	0.014	0.0349
	(0.015)	(3.67)	(0.81)	(0.6)
L.Did	1.613 * * *	0.00786 * * *	0.000256	0.0375 * * *
	(4.72)	(4.37)	(0.1)	(4.26)
Ex	0.833	0.0054	0.00997	0.0085
	(0.33)	(0.4)	(0.51)	(0.13)
Lntexp	8.532 * * *	0.0467 * * *	0.0241	0.221 * * *
	(4.79)	(4.97)	(1.76)	(4.82)
_Cons	185.0 * * *	0.0589	1.073 * *	5.946 * * *
	(4.30)	(0.26)	(3.25)	(5.37)
R^2	0.58	0.55	0.1	0.57
N	252	252	252	252

5. Testing for Heterogeneity

5.1. Grouping Regression

Due to the differences between industries in the US tariff policy on China, this paper further classifies 21 HS section industries and conducts heterogeneity test. In this paper, the industries involved are divided into three categories: Section 1-5 is labor-intensive, Section 6-15 is capital-intensive, and Section 16-21 is technology intensive. Virtual variables of three types of industries are then constructed, and the grouped regression results are shown in Table 6.

Table 6. Group regression results

	(1)	(2)	(3)
	Labor intensive	Capital intensive	Technology intensive
Policy	74.66 * * *	82.88 * *	37.54 * * *
	(-3.6)	(3.26)	(3.62)
Lnexp	7.279 *	5.136 *	2.724
	(-2.66)	(-2.02)	(0.93)
C.Lnexp#C.Policy	3.872 * * *	3.511 * *	1.631 * * *
	(3.89)	(-3.17)	(-3.49)
Ex	1.3	0.575	0.201
	(-0.53)	(0.32)	(-0.08)
_Cons	135.1 *	65.84	108.2
	(2.23)	(1.07)	(-1.55)
N	65	130	78

When analyzing the effect of trade restrictive policy, the results show that Sino-US trade restrictive policy has a positive and significant impact on the industrial chain security of labor-intensive industries, while in capital-intensive and technology-intensive industries, the policy has a negative impact. This indicates that the implementation of the policy interferes with technology exchange, and the impact on capital-intensive and technology-intensive industries with high technology content is greater.

The analysis of cross and cross terms shows that Sino-US trade friction has a negative and significant impact on labor-intensive industrial chain security, while a positive and significant impact on capital - and technology-intensive industries. This may be because labor-intensive industries are more dependent on a stable international trade environment, while for capital - and technology-intensive industries, The occurrence of Sino-US trade frictions has stimulated these industries to take more active countermeasures, such as seeking alternative supply chains, increasing research and development investment to promote independent innovation, and expanding diversified markets, so as to stabilize the industrial chain security.

5.2. The Return of Interactive Items

Given the reduced sample size after segmentation by industry category and the reduced accuracy of the estimated results, it is not possible to tell whether the coefficients between the three groups are significantly different based on the grouping regression results alone. Therefore, this paper introduced the interaction term between the core explanatory variable (cross-multiplicative term) and the industry category dummy variables (lab, cap, tech) into the model. By analyzing the coefficient of the interaction term, the heterogeneous responses of different categories of industries in the face of Sino-US trade policy changes were discussed and quantified [10]. In order to avoid multicollinearity, this paper puts two of the three interaction terms into the model, namely ec_lab and ec_cap.

As shown in Table 7, the three core variables policy are still significant and the model is valid. However, the coefficients of the two cross-fertilization terms are not significant, indicating that the explained variables have a more obvious impact on technology-intensive industries, and the Sino-US trade friction has a greater change on technology-intensive industries. This empirical result is consistent with the policy orientation of the United States towards China, that is, it mainly restricts the export of high-tech products.

Table 7. Regression results of interaction terms

	Coefficient	Std. err.	*t*	*P*>*t*	[95% conf.interval]	
ec_lab	0.0677175	0.0983183	0.69	0.492	0.2613705	0.1259355
ec_cap	0.0141717	0.0737404	0.19	0.848	0.1310713	0.1594147
policy	24.92357	8.721294	2.86	0.005	42.1015	7.745633
lnexp	3.978326	1.633685	2.44	0.016	0.7605317	7.19612
c.lnexp#c.policy	0.9921837	0.3909353	2.54	0.012	0.2221764	1.762191
ex	0.1375766	1.362504	0.1	0.92	2.546086	2.821239
_cons	46.39791	38.54928	1.2	0.23	122.3267	29.53083

6. Summary

Based on the panel data of 21 industries from 2010 to 2022, this paper establishes a DID model, taking the cross-multiplication term of policy dummy variable and export volume to the United States as the core explanatory variable, and the safety factor of China's industrial chain constructed by entropy weight method as the explained variable for benchmark regression. The results show that although the occurrence of Sino-US trade friction has a significant negative impact on China's industrial chain, the subsequent countermeasures in China have effectively dispersed the risks brought by unilateral trade barriers, and the regression coefficient of the cross-multiplication term is still significantly positive.

This paper verifies the stability of the model through robustness test, and further discusses the impact of Sino-US trade frictions on labor, capital and technology-intensive industries through heterogeneity analysis. The conclusion shows that Sino-US trade friction mainly has a negative effect on capital - and technology-intensive industries, and its restrictions on technology-intensive industries are particularly significant.

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