Research on Influencing Factors of Sino-US Trade Based on Principal Component Analysis

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Abstract. This paper focuses on Sino-US trade relations and explores the evolution of key influencing factors in different time periods. A 16-item three-level index evaluation system covering four dimensions—economic, political, technological, and social—was constructed. First, the Pearson correlation coefficient was used to preliminarily screen index data from 2005 to 2023, eliminating indicators with low correlation to Sino-US trade volume. The research period was then divided into two phases using principal component analysis (PCA): 2005–2017 and 2018–2023. Dimensionality reduction was performed for each phase, extracting 1 and 2 key principal components sequentially. The results show that economic and technological factors were the core drivers of Sino-US trade growth during 2005–2017. In the 2018–2023 phase, influenced by intensified trade friction and geopolitics, core drivers shifted significantly: the explanatory power of economic and technological foundations weakened, and the influence of many previously key indicators dropped sharply or became invalid. Political game factors emerged as an independent and important second principal component for the first time, indicating a significant increase in political intervention in Sino-US trade. Based on this, four suggestions are proposed: optimizing export structure to enhance industrial resilience, strengthening technological innovation to consolidate the technical foundation, improving policy mechanisms to optimize the business environment, and expanding diversified markets to reduce external risks. These aim to provide references for addressing the complex landscape of Sino-US trade.

Keywords: Principal Component Analysis; Influencing Factors; Pearson Correlation Coefficient; Sino-US Trade; Trade Friction.

1. Introduction

Against the backdrop of globalization, Sino-US trade relations have become a pivotal part of the world economy, with their stability and growth potential consistently attracting international attention. As economic interdependence among nations deepens, the healthy and stable trade relations between China and the United States—the two largest economies by GDP—are crucial for global economic prosperity and stability. General Secretary Xi Jinping emphasized in the congratulatory letter to the 50th anniversary of the US-China Business Council: "Whether China and the United States can work together to meet challenges concerns the interests of the two peoples and affects the future of humanity" [1].

Since China's accession to the WTO, Sino-US trade relations have undergone remarkable development and changes. The bilateral trade volume between China and the United States surged from $122 billion in 2001 to an astonishing $690.9 billion in 2022 [2], nearly a sixfold increase. This figure exceeds the bilateral trade volume between any other two countries, reflecting the enhanced economic complementarity and interdependence between China and the United States. However, affected by intensified trade restriction policies, sustained tariff barriers, and global supply chain restructuring, Sino-US trade volume in 2023 decreased to $664.5 billion compared with 2022. This volatility further highlights the importance of Sino-US trade relations but also reveals the risks they face. In summary, exploring the key factors influencing Sino-US trade in different time periods is particularly important.

Based on this, this paper first constructs 16 three-level indicators. Secondly, the Pearson correlation coefficient is used to eliminate explanatory variables that have little impact on the explained variable. Next, principal component analysis is applied to divide the period from 2005 to

2023 into two time periods: 2005–2017 and 2018–2023. Principal component analysis is performed on the two time periods to reduce the 17 three-level indicators into 1–2 principal components, identifying the key factors affecting Sino-US trade in each time period to provide suggestions for the government.

2. Literature Review

2.1 Research on Influencing Factors of Sino-US Trade

Hughes and Meckling [4] analyzed the reasons behind the US government's tariffs on Chinese solar producers based on the alliance political model, which helps us understand the trade-off between protectionist policies for manufacturing and reducing renewable energy technology costs. Zhu and Zheng [5] used the GTAP model and WWZ decomposition method to simulate the impact of Sino-US trade friction on global value chains, revealing the path of trade benefit transfer. They suggested that China should strengthen high-tech manufacturing and deepen regional cooperation to upgrade the free trade zone network to cope with trade friction. Wang, Li, and Gao [6] used the quantile grey Lotka-Volterra model to identify the dynamic trade relationship between China and the United States, proposing that the two countries should strengthen cooperation to address trade friction, promote trade balance, and foster the sustainable development of agricultural and food trade.

Chen [11] argued that the US merchandise trade deficit with China is not the cause of the Sino-US trade war but a strategic suppression of China's high-tech industries. Therefore, he suggested that China should respond calmly and enhance independent innovation capabilities to achieve high-quality economic development. Sun Wenhao [17] emphasized the importance of scientific and technological innovation for industrial upgrading and transformation, proposing that China should strengthen basic scientific research and key core technology research. Li Zhou and Ma Yeqing [13] re-accounted for the real Sino-US trade surplus based on export value added, recommending that countries promote the export value-added statistical method, and China should promote the transformation and upgrading of processing trade and reduce dependence on external markets.

2.2 Research on Development Trends of Sino-US Trade

Yan and Cai [7] analyzed the impact of Sino-US trade structure on the real effective exchange rate of the RMB and found that trade structure upgrading increases appreciation pressure, with seasonal and long-term trends. Liu, Yang, CIAIS [8], etc., studied China's food supply sources under Sino-US trade friction, pointing out that shifting to new trading partners can ensure supply while avoiding negative impacts. Xu, Zhong, Zhang [9], etc., emphasized the importance of scientific and technological innovation for industrial upgrading and transformation, suggesting that China should strengthen basic scientific research and key core technology research.

Guo and Wang[14] analyzed the influence of Sino-US economic and trade relations based on trade value added in 2024. They suggested that China should build a regional circulation system focused on the "Belt and Road Initiative," actively lead the reshaping of East Asian regional industrial chains, strengthen economic ties, and guard against the "alliance" of the US and European economies to enhance China's international economic influence. Scholars such as Ma Tianyue and Ding Xuechen [16] analyzed the impact of Sino-US trade friction on imports/exports and global value chains from the perspective of global value chains, finding that the trade war has forced China's industrial upgrading but intensified technological dependence in the short term. Li Feng [12] studied the impact of Sino-US trade friction on China's manufacturing supply chain and countermeasures, proposing that China should stabilize foreign investment and export shares in the short term and build an independent and controllable supply chain system in the medium to long term to enhance endogenous growth capabilities.

3. Comments on Literature Review

In summary, Chinese and foreign scholars have different views on the influencing factors of Sino-US trade. Foreign scholars pay more attention to trade networks and trade policies, while Chinese scholars focus more on trade friction and industrial structure. However, few scholars have conducted segmented research on the key factors of Sino-US trade, and the timeliness of data is insufficient. Based on this, this paper combines the Pearson correlation coefficient and principal component analysis to decompose 2005–2023 into two time periods: 2005–2017, and 2018–2023, to explore the key factors affecting Sino-US trade volume in each period, making up for the deficiencies in previous studies.

3.1 Pearson Correlation Coefficient

The Pearson Correlation Coefficient is an index measuring the linear correlation degree between two variables, widely used in social sciences, natural sciences, economics, and other fields to analyze the correlation between variables, such as height and weight, academic performance and family background. Based on this, this paper constructs 1 first-level index, 4 second-level indices, and 16 third-level indices to study the factors affecting Sino-US trade and their degrees of influence.

The calculation formula of the Pearson correlation coefficient:

$$r = \frac{\sum\left(x-\bar{x}\right)\left(y-\bar{y}\right)}{\sqrt{\sum\left(x-\bar{x}\right)^2\sum\left(y-\bar{y}\right)^2}} \tag{1}$$

3.2 Initial Screening of Indicators and Data Sources

This paper constructs 4 second-level indices and 16 third-level indices to reflect the scale of Sino-US trade. The specific indicators are shown in Table 1:

Table 1 Construction of Indicator System for Influencing Factors of Sino-US Trade

First-Level Index	Second-Level Index	Third-Level Index	Index Explanation	Positive/Negative Index	Unit
Influencing Factors of Sino-US Trade	Economic Factors	China's GDP	The final results of production activities of all resident units in China within a certain period	Positive index	Trillion USD
		US GDP	The final results of production activities of all resident units in the US within a certain period	Positive index	Trillion USD
		Foreign exchange rate	USD/CNY exchange rate	Negative index	
		China's per capita net national income	The total net national income of China divided by its population in the same period	Positive index	USD
		Total China's trade surplus with the US	The total amount by which China's exports to the US exceed imports	Positive index	Billion USD

	Total flow of China's direct investment in the US	The annual scale of China's direct investment in the US	Positive index	Billion USD
	China's trade openness	The proportion of China's import and export trade volume in the annual GDP within a certain period	Negative index	
Political Factors	Sino-US bilateral relations	Scores of Sino-US relations from the Institute of International Relations, Tsinghua University	Negative index	Points
	Number of Sino-US summit meetings	The number of meetings between Chinese and American leaders from 2002 to 2023	Negative index	Times
	Number of patent applications in China	The number of technologies with independent intellectual property rights in China	Positive index	10,000 pieces
	Full-time equivalent of researchers in China's R&D	The sum of full-time personnel and part-time personnel converted into full-time personnel according to work volume	Positive index	10,000 person-year
Technological Factors	US high-tech imports to China	US imports of products with high R&D intensity to China, such as pharmaceuticals, scientific instruments, electrical machinery, etc., denominated in USD	Positive index	Billion USD
	China's high-tech imports from the US	China's imports of products with high R&D intensity from the US, denominated in USD	Negative index	Billion USD

Social Factors	Number of US arrivals	The number of foreigners entering China for visiting friends, medical treatment, shopping, or engaging in cultural, sports, religious activities, etc.	Positive index	10,000 persons
	China's population size	Refers to inbound tourists during the reporting period, including foreigners visiting friends, seeking medical treatment, shopping, or engaging in cultural, sports, or religious activities in the United States.	Positive index	10,000 persons
	US unemployment rate		Negative index	

The above data are all from the World Bank WDI database (datatopics.worldbank), China National Database (data.stats), UNcomtrade (comtradeplus), etc. This is time-series data from 2005 to 2023.

3.3 Empirical Analysis of Pearson Correlation Coefficient

The above indicators were standardized to eliminate the influence of inconsistent units and other factors. Then, the Pearson coefficient was used to analyze the correlation between each third-level index and the first-level index (i.e., Sino-US trade) in each year. The specific values are shown in Table 2:

Table 2 Pearson Correlation Coefficients

Label	Explanatory Variable	2005–2017	2018–2023
X_1	China's GDP	0.980**	0.681**
X_2	US GDP	0.910**	0.711**
X_3	Foreign exchange rate	-0.862**	-0.285*
X_4	China's per capita net national income	0.977**	0.726**
X_5	Total China's trade surplus with the US	0.975**	0.462*
X_6	Total flow of China's direct investment in the US	0.751**	-0.001
X_7	China's trade openness	-0.961**	-0.119
X_8	Sino-US bilateral relations	-0.286*	0.649**

X_9	Number of Sino-US summit meetings	-0.380**	-0.677**
X_{10}	Number of patent applications in China	0.933**	0.894**
X_{11}	Full-time equivalent of researchers in China's R&D	0.988**	0.612**
X_{12}	US high-tech imports to China	0.959**	-0.106
X_{13}	China's high-tech imports from the US	0.959**	-0.106
X_{14}	Number of US arrivals	0.764**	-0.157
X_{15}	China's population size	0.979**	0.285
X_{16}	US unemployment rate	-0.061	-0.357**

Note: *** indicates significance at the level of 0.001, ** indicates significance at the level of 0.01, and *
indicates significance at the level of 0.05.

According to the results, in 2005–2017, the absolute values of the correlation coefficients between X_8 (Sino-US bilateral relations), X_9 (number of Sino-US summit meetings), and X_{16} (US unemployment rate) and Sino-US trade volume were lower than 0.6, so these indicators were removed. Similarly, in 2018–2023, X_3 (foreign exchange rate), X_5 (total China's trade surplus with the US), X_6 (total flow of China's direct investment in the US), X_7 (China's trade openness), X_{12} (US high-tech imports to China), X_{13} (China's high-tech imports from the US), X_{14} (number of US arrivals), X_{15} (China's population size), and X_{16} (US unemployment rate) were removed.

4. Principal Component Analysis

4.1 Principle of Principal Component Analysis

Principal Component Analysis (PCA) is an efficient data dimensionality reduction technique that transforms multiple highly correlated indicators in the original dataset into a smaller number of principal components. These principal components can effectively retain and reflect most of the information in the original data, thus eliminating the multicollinearity of independent variables. Based on this, this paper will use PCA technology to perform dimensionality reduction on the many influencing factors of Sino-US trade volume, aiming to construct a function dimensionality reduction model to integrate various factors, making the constructed evaluation system more in line with the actual situation. The following is a brief explanation of PCA technology:

Suppose there are sample data of n years and m indicators related to Sino-US trade, then the initial sample matrix can be obtained as:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix} = (x_{ij})_{n\times m} \tag{2}$$

where i = (1, 2, ..., n) represents the i-th row of the initial sample matrix, and j = (1, 2, ..., m) represents the m-th column. The definitions of i and j in the following text are the same as here.

4.1.1 Construction of Correlation Coefficient Matrix R=（rij）n×m

The calculation formula of r_{ij} is:

$$r_{ij} = \frac{1}{n}\sum_{i=1}^{n}\frac{(x_{ij}-x_i)(x_{ij}-x_j)}{s} \tag{3}$$

where s represents the sample variance.

4.1.2 Solution of Eigenvalues and Eigenvectors

The eigenvalues of R can be calculated according to the characteristic equation |R-λI|=0. R represents the correlation coefficient matrix, and I represents the identity matrix. Arranged in descending order of λ, we can get λ_1， λ_2， ......λ_n, and the eigenvectors a_j can also be calculated.

4.1.3 Calculation of Contribution Rate and Cumulative Contribution Rate

The contribution rate refers to the percentage of the total variance explained by the nth principal component in the total variance of the entire dataset. The specific formula is:

$$e_i = \frac{\lambda_i}{\sum_{i=1}^{p}\lambda_i} \tag{4}$$

The cumulative variance contribution rate refers to the percentage of the total variance explained by the first n principal components in the total variance of the entire dataset. The specific formula is:

$$E_m = \frac{\sum_{i=1}^{m}\hat{\lambda}_i}{\sum_{i=1}^{p}\hat{\lambda}_i} \tag{5}$$

4.1.4 Calculation of Principal Component Scores

$$z_m = a_{mj}x_j \tag{6}$$

4.1.5 Selection of Principal Components

In principal component analysis, the number of principal components is determined by calculating the cumulative variance contribution rate of each principal component. Usually, principal components with a cumulative variance contribution rate ≥85% are selected, as these principal components are generally considered to fully represent the information in the original dataset. Based on this method, we can effectively reduce the data dimension while retaining the information of the original dataset to the greatest extent. Next, through these extracted principal components, we will construct an index system for the influencing factors of Sino-US trade volume to deeply analyze the potential factors of its changes.

4.2 Empirical Test

4.2.1 KMO and Bartlett's Sphericity Test

The KMO test and Bartlett's sphericity test are two key steps in evaluating the suitability of data before factor analysis. The core of the KMO test is to quantify the richness of common factors among variables by comparing the correlation coefficients and partial correlation coefficients between variables, so as to judge whether the data are suitable for factor analysis; the KMO value is an intuitive index, ranging from 0 to 1, used to judge whether the data are suitable for factor analysis. A KMO value greater than 0.9 indicates very suitable, 0.8–0.9 indicates more suitable, 0.6–0.8 indicates acceptable, and below 0.5 indicates that factor analysis is not appropriate. The KMO values for 2005–2017 and 2018–2023 are shown in Table 3 and Table 4, respectively. Among them, through testing, in the indicators of 2005–2017, X_{13} would lead to a non-positive definite correlation coefficient matrix due to its strong correlation with other variables, so X_{13} was removed in this stage; similarly, X_9 and X_{11} were removed in the indicators of 2017–2023.

Table 3 KMO Values of Data from 2005 to 2017

KMO Sampling Adequacy Measure		0.657
Bartlett's Test of Sphericity	Approximate Chi-Square	431.936
	Degrees of Freedom	66
	Significance	0.000

Table 4 KMO Values of Data from 2018 to 2023

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.641
Bartlett's Test of Sphericity	Approximate Chi-Square	29.278
	Degrees of Freedom	10
	Significance	0.001

The validity test results show that the KMO values of the data for the two periods are 0.657 and 0.641, both greater than 0.6, and the significance of the Bartlett's sphericity test statistics is less than 0.001, reaching the significance level; this indicates that the data are suitable for factor analysis.

4.2.2 Empirical Analysis

Using SPSS26.0, through the following steps: "Analysis—Dimension Reduction—Factor," the principal component analysis results were obtained, and the principal component variance explanation tables are shown in Table 5 and Table 6:

Table 5: Explanatory Table of Principal Component Variances from 2005 to 2017

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	Percentage of Variance	Cumulative %	Total	Percentage of Variance	Cumulative %
1	10.597	88.309	88.309	10.597	88.309	88.309
2	0.802	6.682	94.992			
3	0368	3.065	98.057			
4	0116	0.963	99.020			
5	0.079	0.654	99.674			
6	0.031	0.258	99.932			
7	0.006	0.052	99.984			
8	0.001	0.009	99.993			
9	0.001	0.006	99.999			
10	7.550E-	0.001	100.000			
11	5.987E-	4.990E-5	100.000			
12	3.546E-	2.955E-5	100.000			

Extraction Method: Principal Component Analysis.

Table 6: Explanatory Table of Principal Component Variances from 2018 to 2023

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	Percentage of Variance	Cumulative %	Total	Percentage of Variance	Cumulative %
1	4.174	83.472	83.472	4.174	83.472	83.472
2	0.606	12.112	95.584	0.606	12.112	95.584
3	0.212	4.240	99.824			

4	0.006	0.128	99.952
5	0.002	0.048	100.000

Extraction Method: Principal Component Analysis.

From the principal component variance analysis, it can be seen that in the principal components of 2005–2017, the first principal component explained 88.309% of the total variance >85%, indicating that it can represent the main information of the influencing factors of Sino-US trade. In the principal components of 2018–2023, the first principal component explained 83.472% of the total variance, and the first and second principal components together explained 95.584% of the total variance, indicating that these two principal components together can represent the main information of the influencing factors of Sino-US trade.

In addition, scree plots were drawn for the principal component extraction data of the two periods, as shown in Figure 1 and Figure 2:

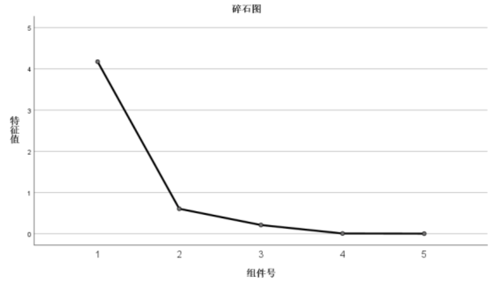

Figure 1 Scree Plot of Principal Components for 2005–2017

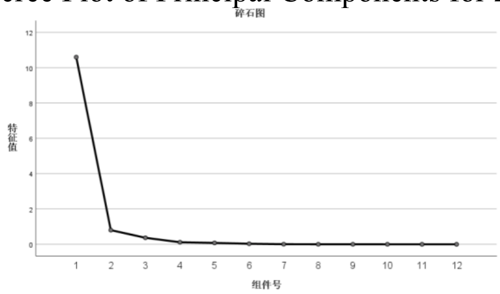

Figure 2 Scree Plot of Principal Components for 2018–2023

As shown in Figure 1, the slope of principal component 1 is relatively large, indicating that it contains more information, so the first principal component should be extracted. As shown in Figure 2, the slopes of the first two principal components are relatively large, so the first two principal components are extracted. Then, the score coefficient tables for the two periods of data were obtained, as shown in Table 7 and Table 8, respectively:

Table 7: Score Coefficient Table of Data from 2005 to 2017

	Component
	1
X1	0.997
X2	0.969
X3	-0.765
X4	0.994
X5	0.951
X6	0.833
X7	-0.963
X10	0.982
X11	0.995
X12	0.976
X14	0.815
X15	0.997

Extraction Method: Principal Component Analysis.

a. 1 component extracted.

Table 8: Score Coefficient Table of Data from 2018 to 2023

	Component	
	1	2
X_1	0.947	-0.319
X_2	0.975	-0.119
X_4	0.973	-0.217
X_8	0.748	0.646
X_{10}	0.906	0.161

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Based on the above data, a principal component formula was obtained to reflect the effects of various influencing factors on Sino-US trade volume in 2005–2017:

$$F_1=0.997X_1+0.969X_2-0.765X_3+0.994X_4-0.951X_5+0.833X_6-0.963X_7+0.982X_{10}+0.995X_{11}+-0.976X_{12}+0.815X_{14}+0.997X_{15} \tag{7}$$

Similarly, for the data of 2018–2023, there is a principal component formula:

$$F_2=0.947X_1+0.975X_2+0.973X_4+0.748X_8+0.906X_{10} \tag{8}$$

5. Conclusions

This paper constructs an index system spanning four dimensions—economic, political, technological, and social—and employs principal component analysis (PCA) to empirically investigate the factors influencing Sino-US trade during two distinct phases: 2005–2017 and 2018–2023. By analyzing the data characteristics of principal component indicators across different stages, the study identifies the key drivers of trade dynamics, providing a basis for continuously adjusting China's trade policies toward the United States and offering actionable recommendations for policymakers.

(1) 2005–2017: Dual-Driven by Economic and Technological Forces

The core factors during this period include economic and technological indicators such as X_1 (China's GDP), X_2 (US GDP), X_{11} (Full-time Equivalent of R&D Personnel), and X_{10} (Number of Invention Patents), which collectively explain 88.3% of the variance in Sino-US trade volume. This suggests that trade growth during this phase primarily relied on the expansion of economic aggregates and technological innovation in both countries. The underlying reasons can be attributed to China's successful accession to the WTO in 2001, which deepened its integration into the global economy. During this period, China's per capita net national income (X_4) increased, boosting domestic purchasing power and driving up imports from the US. For example, after the 2008 financial crisis, China increased its holdings of US Treasury bonds by over $1 trillion, stabilizing the US dollar's creditworthiness. Additionally, China accumulated trade surpluses through exports of low- to mid-tech products (X_5: Total Trade Surplus with the US) while relying on high-tech imports from the US (X_{12}: US High-tech Exports to China), reflecting a complementary trade structure. Notably, X_3 (USD/CNY Exchange Rate) exhibited an inverse relationship with trade volume, seemingly contradicting the traditional trade theory that currency depreciation stimulates exports. This paradox highlights the specialty of the Sino-US trade structure, where Chinese exports heavily depend on imported intermediate goods. A weaker RMB increases import costs, thereby eroding the price competitiveness of Chinese exports.

(2) 2018–2023: Multidimensional Reconfiguration Dominated by Political Games

The principal components during this stage exhibit distinct characteristics:

Economic-technological foundations: Positive indicators such as X_1 (China's GDP), X_2 (US GDP), and X_{10} (Number of Invention Patents) remained core drivers but with diminished explanatory power (83.5%), signaling a weakening of traditional economic forces. Comparative analysis of the two phases reveals that most indicators significantly influencing trade volume in 2005–2017 saw their impact sharply decline or become irrelevant after 2018, including X_3 (Exchange Rate), X_5 (Trade Surplus), X_6 (Direct Investment Flow), X_{12} (US High-tech Exports to China), and X_{13} (China's High-tech Imports from the US). The diminished relevance of X_3, X_5, and X_6 can be attributed to the Trump administration's aggressive tariff hikes on Chinese goods, which offset the effects of exchange rates and profoundly reshaped bilateral trade. In 2019, the first year of the "trade war," China's annual trade deficit with the US shrank by 18%, compared to just 1% in previous years. High-tech trade was particularly hard-hit, with the US imposing sanctions on over 600 Chinese enterprises by October 2023—a figure that climbed to over 900 by March 2025.

Political intervention: X_8 (Sino-US Bilateral Relations, loading 0.646) emerged as an independent principal component for the first time (contributing 12.1%), confirming the direct role of political games in shaping trade flows post-friction. This shift indicates that Sino-US trade relations entered a new phase under Trump, with Biden's administration maintaining a core strategy of containing China, albeit with less rhetorical aggression. As Trump returned to power in 2025, this trend is expected to persist.

6. Recommendations

6.1 Optimize Export Structure and Enhance Industrial Resilience

Customs data show that low-value-added products such as textiles and furniture still account for over 20% of China's exports to the US. Therefore, shifting the export mix toward high-value-added, high-tech products remains a strategic priority. First, accelerate the digital and green transformation of China's manufacturing sector, focusing on emerging technologies such as artificial intelligence, new energy vehicles, and biotechnology. Build end-to-end manufacturing ecosystems to enhance the competitiveness of high-value products. Leverage China's global leadership in new energy vehicles, photovoltaics, and rare earth resources to capture higher value-added segments. For instance, dominate battery technology in electric vehicles, maintain innovation in photovoltaics, and deepen rare earth processing. Adopt the export value-added statistical system to replace traditional gross trade accounting, accurately reflect trade profits allocation， and mitigate frictions arising from statistical biases [7]. Adapt to global trends and continuously upgrade the export structure to ensure sustainable trade growth.

6.2 Strengthen Innovation-Driven Development and Solidify Technological Foundations

In the China-US trade war, technological blockade can be said to be the United States' biggest reliance. If China wants to gain the initiative in Sino-US trade, it must accelerate its pace of catching up in the field of high technology. First and foremost, it should increase investment in basic research and key core technologies to promote the transformation from technological catch-up to technological leadership. It can enhance the technological advantages of domestic enterprises in global competition by increasing the government's financial support for scientific research institutions and encouraging enterprises to increase R&D investment, especially in cutting-edge technological fields such as artificial intelligence, semiconductors, and quantum computing. It can utilize the "export first-mover effect" to force innovation, taking advantage of the short-term surge in orders to reduce the marginal cost of R&D and accelerate technological iteration [9]. At the same time, it can strengthen cooperation with global scientific research institutions and universities to promote technological exchanges and joint research and development. In the context of increasingly fierce global technological competition, open international cooperation is more conducive to breaking down technological barriers. Innovation is the core of development in the contemporary era, and only by valuing innovation can there be real development.

6.3 Improve Policy Mechanisms and Optimize the Business Environment

Strengthening the reform of the policy system and optimizing the business environment are the policy needs demonstrated by China in responding to the China-US trade war. China should continue to deepen the reform of "streamlining administration, delegating power, improving regulation, and strengthening services". By simplifying the administrative approval procedures and reducing administrative costs, the complexity for enterprises in handling affairs can be reduced. Secondly, it is necessary to optimize tax and financial policies for foreign trade enterprises through policy subsidies and tax incentives [23], so as to promote further inflow of foreign capital and the expansion of domestic enterprises. Moreover, financial institutions should provide more convenient financing channels to support technological innovation and industrial upgrading of enterprises, especially small and medium-sized enterprises. Local governments should establish a "one-stop service" platform for enterprises to ensure the efficiency and fairness of policy implementation. In addition, it is necessary to strengthen intellectual property protection and further improve the legal framework for intellectual property rights to ensure that technological innovation achievements are effectively protected. A strong policy guarantee is the ballast stone for the competitiveness of the business environment, and a sound business environment can stimulate the innovation and creativity of enterprises, thereby enhancing their core competitiveness.

6.4 Diversify Markets and Reduce External Risks

In the face of the trade war, it is particularly important to reduce the risks of relying on a single market by expanding trade partners and actively participating in the division of labor in the global value chain. First, China should strengthen the implementation of the "Belt and Road" Initiative and deepen trade cooperation with developing countries and emerging market countries. It can sign package agreements covering "resources, technology, and markets" through mechanisms such as RCEP and BRICS [24]. Cooperation with countries in Asia, Africa, and Latin America can effectively reduce dependence on the U.S. market. China can find more opportunities for economic growth in emerging markets while mitigating the risks brought by economic fluctuations in developed countries. Furthermore, China should enhance trade cooperation with mature markets such as Europe and Australia, especially in high technology, green technology, and advanced manufacturing, aiming to gain a more favorable position in the global high-end industrial chain. A diversified market strategy helps cope with the uncertainties in international trade and maintain economic growth amid the China-U.S. trade war.

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