Investigating the Correlation between Fluctuations in the U.S. Stock Industry Index and U.S. Import-Export Volume Fluctuations using the Dynamic Time Warping (DTW) Method

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Abstract. Affected by the COVID-19 epidemic and the global economic turmoil, the total amount of US imports and exports and the various indexes of US stocks have fluctuated greatly in recent years. As one of the largest economies in the world, the fluctuation of the economic situation of the United States shows the global economic situation to a certain extent, and the total amount of import and export is one of the important indicators. From the theoretical research, there is an indirect economic relationship between the total import and export volume and the industry index, and the fluctuation correlation between the two is supported by economic theory. From the empirical research, this paper uses Log Return and Dynamic Time Warping (DTW) model to analyze and visualize the total volume of US imports and exports and ten typical industry indexes of US stocks. It is found that there is a uniform correlation between the trend of various indexes and the trend of total import and export volume, and there is a correlation law between them. However, there is no industry that is extremely close to the development trend of total imports and exports.

Keywords: Dynamic Time Warping (DTW), Log return, Stock Industry Index, Total Imports and Exports

1 Introduction

In recent years, the global economy has been volatile due to the COVID-19 pandemic. The U.S., as one of the world's largest economies, is influenced by the global economic situation, impacting its total imports and exports. Fluctuations, recessions, and recoveries in the global economy affect the value of U.S. imports and exports. Additionally, exchange rate and trade policy changes contribute to unstable fluctuations in U.S. import and export patterns. Furthermore, different industries, such as the energy equipment and service industry and the commodity services and supplies industry, experience irregular fluctuations in their overall industry index. This leads to noticeable price fluctuations in U.S. stock enterprises within these industries. This paper aims to identify

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the correlation between various indicators in these irregular economic fluctuations and examine the relationship between macro import/export volume and specific micro stock indices.

From an economic standpoint, imports and exports do not directly impact individual stock changes. However, by analyzing the exchange rate and integrating individual stock prices by industry, we can observe the correlation between them. Thorbecke and Sengonul [9] (2023) conducted a nonlinear autoregressive analysis on Turkey's total import and export volume and exchange rate, revealing different relationships at different stages. Appreciation of the exchange rate led to increased import and export, while changes in the exchange rate during depreciation periods often had no effect on trade.

Kemal and Qadir [4] (2005) examined the long-term and short-term relationship between import, export, and exchange rate, finding a significant correlation. The real exchange rate was negatively correlated with exports and positively correlated with imports.

Exchange rates and stock prices are both products of the financial market and are closely intertwined. Zhao [10] (2010) conducted a study on the cross-volatility effect between the foreign exchange market and the stock market, using the likelihood ratio statistic. The research revealed a two-way volatility spillover effect between the two markets.

Furthermore, the industry sector index in this study represents the integrated statistics of stock prices from listed companies within the industry. By consolidating stock prices from various industries, the industry sector index provides a more comprehensive and intuitive representation of industry development trends and the current status quo. The basic logical relationship of research objects can be shown in Figure 1.

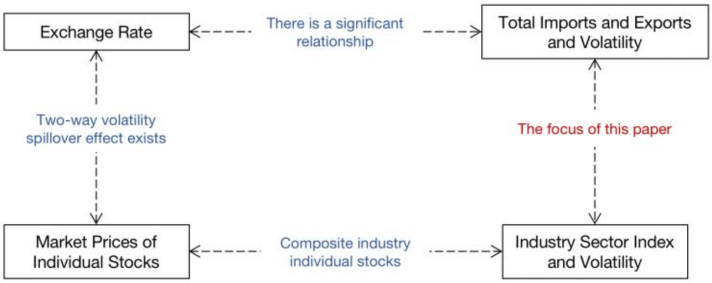

Fig. 1. Basic Logic Diagram

By analyzing recent data, fitting models, and examining various industries, conclusions can be drawn, offering investors multiple perspectives and a stronger foundation for investment analysis. Moreover, industries differ in their plate index and total import and export law, resulting in varying levels of impact. Thus, industry stability can be achieved through conclusions, while companies can gain insights into industry trends and adjust accordingly through regularity analysis. Additionally, this research provides a theoretical basis for policy adjustments at the national level. Lastly, the mathematical methods employed in this study have financial implications and offer a new reference for exploring the relationship between "industry sector index," "total import and export volume," and "volatility" for academic researchers.

2 Methodology

2.1 Theoretical logic study

Innovation and exports are key drivers of economic growth (Bołkunow [2], 2019; Pla-Barber and Alegre [7], 2007). Import and export, known as one of the "troika" of economic development, play a vital role in economic growth. Reduced exports have adverse effects on the economy, suppressing enterprise efficiency and impacting stock prices. This negative impact can be seen in various ways.

Firstly, reduced export volumes directly affect the profitability and survival of domestic enterprises, especially those reliant on exports, potentially leading to capacity reduction, layoffs, and closures, which negatively affect the job market. Secondly, reduced export volumes have negative implications for trade surplus and foreign exchange reserves. A decrease in exports expands the trade deficit, affecting the country's balance of payments. A large trade deficit can trigger currency depreciation, inflationary pressure, and a decline in international credit, exacerbating economic instability. Additionally, reduced exports have a ripple effect on domestic industrial and supply chains, affecting production and employment in related industries. This ripple effect can spread throughout the economy, negatively impacting overall economic growth. In an economic downturn, poor enterprise performance raises concerns among investors, leading to a decline in stock prices. This decline in stock prices can affect investor confidence, inhibiting investment and economic recovery.

The export volume of foreign trade enterprises has a significant impact on their operating efficiency. When export volumes decrease, companies face challenges such as falling sales, suppressed profits, lower capacity utilization, and higher costs, which weaken their profitability. This adverse situation causes investors to worry about the company's outlook, negatively impacting the stock price. Moreover, the reduction of export volume also affects related enterprises, including suppliers of raw materials and parts, as well as industries like logistics, transportation, and packaging. Conversely, increasing export volumes have the opposite effect, boosting sales, profitability, and investor confidence, which positively impacts share prices and related companies (Pagell and Shevchenko [6], 2014; Bernard [1] et al., 2007).

2.2 Data source and processing

Data source and selection.

The data in this paper mainly comes from the *TongHuaShun iFinD* financial data terminal, which is widely used in financial research. It provides international financial data and industry research analysis, making it highly regarded in the financial market. The data used in this article, including the total amount of U.S. imports and exports, is sourced from *iFinD*. The data covers the period from January 31, 2019, to May 31, 2023, with a monthly granularity over 53 months. Figure 2 displays the raw data of the total amount of imports and exports. By comparing it with the overall trend and considering the industry's development, this paper selects the total import and export of the U. S. as the main control data.

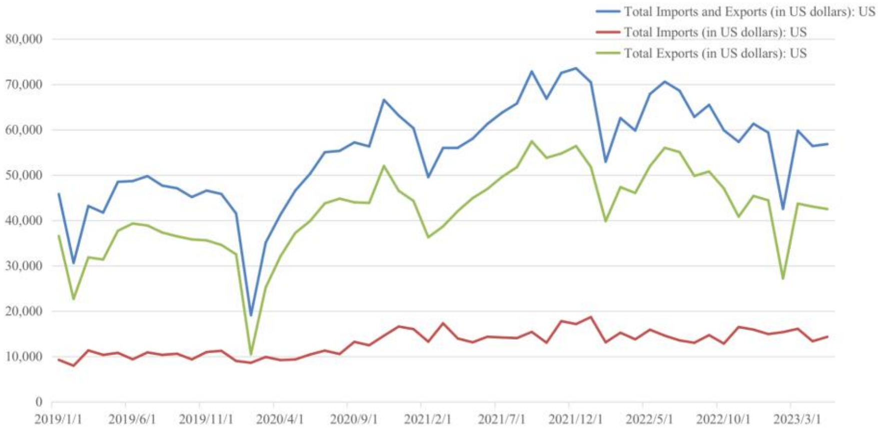

Fig. 2. U.S. Import, Export, and total Import and Export Data from January 2019 to May 2023

The industry indexes used in this paper, such as energy equipment and services (861001.TI), building materials (861004.TI), and others, are issued by internal subsidiaries of the platform. These indexes cover numerous companies and provide authoritative weight allocation to reflect the development of the US stock market's industries. To comprehensively analyze the correlation between total import and export volume and industries, this paper selects ten typical industries as cases: six related to industrial manufacturing and four related to consumer goods. Table 1 displays the specific industry indicators discussed in this paper.

Table 1. Ten Industry Index Details

Industry Name	Industry Code	Share Number	Constituent stock representative
Energy Equipment and Services	(861001.TI)	56	(SLB.N)
Building Materials	(861004.TI)	15	(CRH.N)
Chemicals	(861003.TI)	84	(LIN.N)
Oil and Gas	(861002.TI)	206	(XOM.N)
Metals and Mining	(861006.TI)	151	(BHP.N)
Machine Building	(861013.TI)	120	(CAT.N)
Business Services and Supplies	(861015.TI)	66	(WM.N)
Cars	(861023.TI)	43	(TSLA.O)
Electronic Equipment and Instruments	(861056.TI)	138	(APH.N)
Consumer Goods Distribution and Retail	(861033.TI)	41	(WMT.N)

Data processing.

To avoid data analysis challenges arising from differing bases, the Log Return method, from the equation (1), commonly employed in financial time series models, is used to process the data of total import and export as well as ten industry indexes. Consider two time points, T1 and T2, where the asset price is P1 and P2, respectively.

$$Log\ Return = \ln\left(\frac{P_1}{P_2}\right) \tag{1}$$

The value of log return represents the proportion of the relative price change from P1 to P2 over time. It captures the relative increase or decrease in price, rather than just the absolute difference. Log return enables comparisons between assets or portfolios by translating absolute price changes into relative changes.

2.3 Model principle

Dynamic Time Warping (DTW) is a method for comparing the similarity between two time series. It can measure the degree to which shapes and movements are similar between two time series, even if they differ in length and speed. The basic idea of DTW is to find the best match between two time series by aligning each point in time to minimize the distance or difference between them.

DTW, originally designed for speech recognition (Sakoe and Chiba [8], 1978), has been widely used in various fields such as finance and geographic exploration. For instance, Nakagawa [5] et al. (2019) used the DTW model combined with TOPIX to predict the monthly stock change trend effectively. Similarly, He [3] et al. (2023) applied the DTW model and found a moderate correlation between students' navigation patterns and their reading proficiency.

To compare the similarity of two sets of data, such as the first set 1,1,3,3,2,4 and the second set 1,3,2,2,4,4, the traditional Euclidean distance algorithm can be used. By corresponding the data points according to the time series and performing algebraic operations, the Euclidean distance of this example is 6 (Figure 3). In this case, from the equation (2)(3)(4), the first set of data is sequence Q with length n, the second set is sequence C with length m, and the matrix M represents Euclidean distances, where M(i,j) stands for the distance between the i-th element of Q and the j-th element of C when i=j.

$$Q = [q_{1,}q_2, \dots, q_n] \tag{2}$$

$$C = [c_1, c_2, \dots, c_m] \tag{3}$$

$$M(i,j) = |Q(i) - C(j)|\ , minimum\ quantity \le i,j \le maximum\ quantity \tag{4}$$

If the points of a sequence are allowed to correspond to multiple consecutive points of another sequence, this algorithm is called time warping. In the program, the steps of the DTW algorithm are:

1.Calculate the distance matrix between stores in two sequences.

2.Find a path from the upper left corner of the matrix to the lower right corner that minimizes the sum of all elements in the path. Assuming that the shortest path length is L_{min} (i, j), the shortest path length can be found by recursive algorithm.

At the same time, the path length of the matrix from the lower left corner to the upper right corner has the following properties:

1.Current path length = previous path length + current element size.

2.The preceding element of an element (i, j) on the path can only be one of the adjacent elements (i, j-1) on the left, (i-1, j) on the upper, or (i-1, j-1) on the upper left. From the equation (5)(6).

$$L_{min}(1,1) = M(1,1) \tag{5}$$

$$L_{min}(i,j) = \min\{L_{\min}(i,j-1), L_{min}(i-1,j), L_{min}(i-1,j-1)\} + M(i,j) \tag{6}$$

From the Figure 3, the dynamic time distance is 0, Which is less than the Euclidean distance.

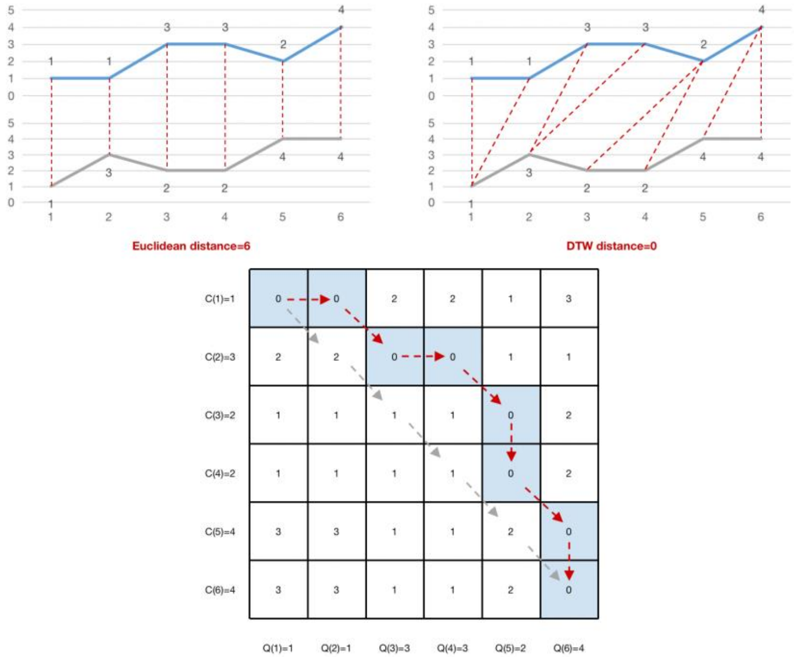

Fig. 3. Comparison of Euclidean distance and dynamic time warping distance

DTW is suitable for analyzing time series with different lengths and speeds due to its ability to handle non-linear alignment. It is robust to noise and outliers by considering global information. Thus, the DTW model is suitable for analyzing exponential fluctuations. When other conditions are equal, a shorter DTW distance indicates a closer relationship and higher similarity between the two trend lines.

2.4 Empirical study

The DTW model simulation in this study uses Python code due to the large data volume. The optimal route and shortest distance are calculated using a recursive algorithm and function construction. The resulting alignment path allows for sequence comparison and analysis, as it represents the order in which two sequences need to be aligned. This alignment enables visualizing the original image and path, facilitating a better understanding of similarities and differences between the sequences.

The concrete steps of empirical research are as follows:

1.The value of the ten industry indexes after log return is matched with the volatility of the total import and export volume.

2.Generate DTW paths and distances through code programs and perform sequence alignment. Each set of data is recorded and visually analyzed.

3 Results and discussion

Table 2 displays the DTW distance for ten industry sector indexes compared to the volatility of total U.S. imports and exports. A smaller DTW distance indicates a higher similarity between the trendlines. The table reveals that the distance index for the ten industries generally falls within the range of 4.2 to 5.0, with no significant difference between the industrial manufacturing and consumer goods sectors. Among the industrial goods manufacturing industry, Metals and Mining and Chemicals exhibit the most similar trend changes to the total import and export volume, while Energy Equipment and Services show a more distinct difference. Within the consumer goods sector, Business Services and Supplies display a significantly closer alignment. Overall, the correlation between the index change of various industries and the change in total import and export volume remains stable from 2019 to 2023. No industry demonstrates a high level of synchronization or complete detachment from the total import and export volume.

Table 2. Ten Industry Index DTW distances

PAIRING OBJECT		DTW DISTANCE
Total Imports and Exports (in US dollars): US	Energy Equipment and Services	4.9094
	Building Materials	4.4818
	Chemicals	4.3673
	Oil and Gas	4.7549
	Metals and Mining	4.3598
	Machine Building	4.6654
	Business Services and Supplies	4.2238
	Cars	4.5113
	Electronic Equipment and Instruments	4.7335
	Consumer Goods Distribution and Retail	4.8700

In order to more intuitively show the similarity between the trend line of each industry and the trend line of the total amount of imports and exports, visual analysis is used to show it. Each study will give two sets of data raw trend line, DTW path, aligned sequence drawing. In this paper, energy equipment and services as a case for visual analysis. Details are shown in Figure 4.

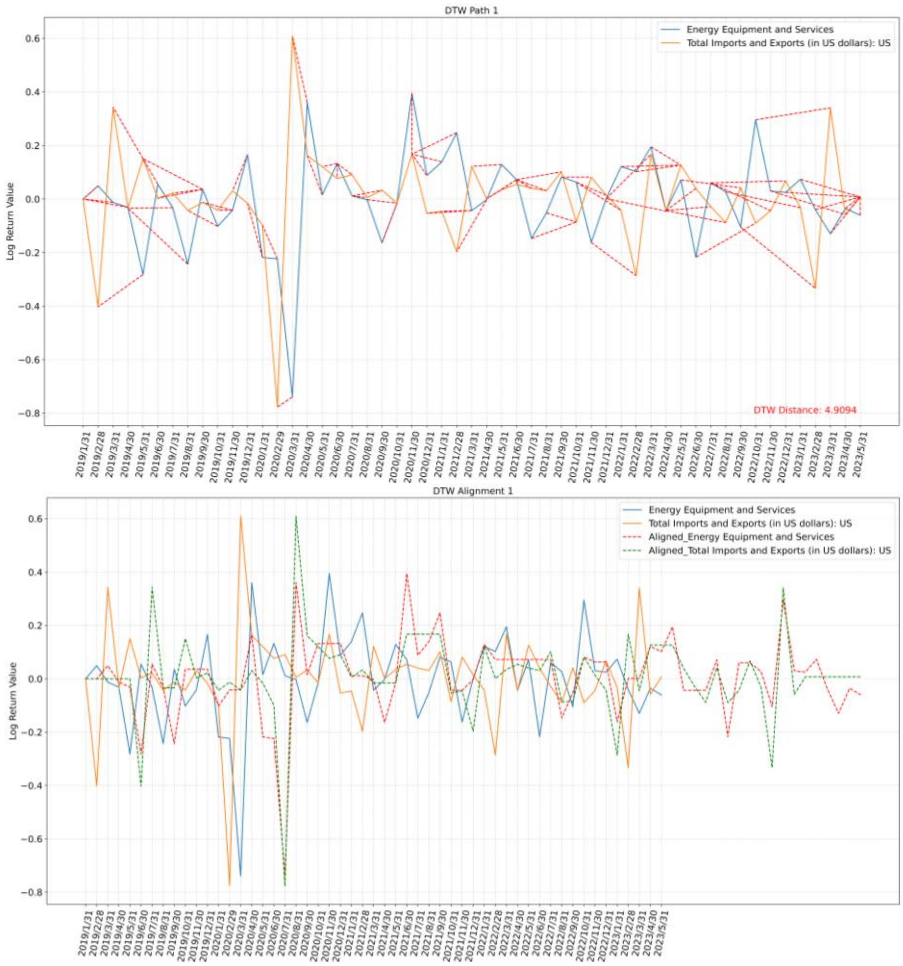

Fig. 4. The Energy Equipment and Services industry index trends, DTW paths, alignment sequence

4 Conclusion

According to the empirical research data, the trend similarity between the industry index and the total import and export volume of the United States is inconsistent. Industries need to continue to pay attention to macro policies and national government data to stabilize the industry market, but internal adjustments can be made through regularity analysis. Among the ten typical industries, the index trend line of no industry is highly consistent with the trend line of total import and export volume, which indicates that it is unrealistic for investors to invest in a specific industry by directly observing the trend of total import and export volume, and they also need to understand the internal development of the industry and the international situation. The application of DTW model combines mathematics with financial market to a certain extent, which is a good interdisciplinary exploration.

Reference

1. Bernard, A. B., Jensen, J. B., Redding, S. J., & Schott, P. K. (2007). Firms in international trade. Journal of Economic Perspectives, 21(3), 105-130.
2. Bołkunow, W., (2019). Internationalization of European small and medium-sized companies. En M. H. Bilgin, H. Danis, E. Demir, & U. Can (Eds.), Eurasian Business Perspectives. Springer International Publishing, pp. 39–51.
3. He, Q., Borgonovi, F. and Suárez-Álvarez, J. (2023) "Clustering sequential navigation patterns in multiple-source reading tasks with dynamic time warping method," Journal of computer assisted learning, 39(3), pp. 719–736.
4. Kemal, M.A. and Qadir, U. (2005) "Real Exchange Rate, Exports, and Imports Movements: A Trivariate Analysis," Pakistan development review, 44(2), pp. 177–195.
5. Nakagawa, K., Imamura, M. and Yoshida, K. (2019) "Stock price prediction using k-medoids clustering with indexing dynamic time warping," Electronics and communications in Japan, 102(2), pp. 3–8.
6. Pagell, M., & Shevchenko, A. (2014). Why research in sustainable supply chain management should have no future. Journal of Supply Chain Management, 50(1), 44-55.
7. Pla-Barber, J., Alegre, J., (2007). Analysing the link between export intensity, innovation and firm size in a science-based industry. Int. Bus. Rev. 16 (3), 275–293. https://doi.org/10.1016/j.ibusrev.2007.02.005.
8. Sakoe, H., & Chiba, S. (1978). Dynamic programming algorithm optimiza- tion for spoken word recognition. IEEE Transactions on Acoustics, Speech, and Signal Processing, 26, 43–49. https://doi.org/10.1109/ TASSP.1978.1163055.
9. Thorbecke, W. and Sengonul, A. (2023) "The impact of exchange rates on Turkish imports and exports," International economics (Paris), 174, pp. 231–249.
10. Zhao, H. (2010) "Dynamic relationship between exchange rate and stock price: Evidence from China," Research in international business and finance, 24(2), pp. 103–112.