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Econometric evaluation of the China–US trade war effects☆

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ABSTRACT

The escalating trade war between China and the US, initiated in 2018, has significantly impacted the trade pattern of these two nations. This event can be treated as an intervention which has led to a series of retaliatory actions, resulting in substantial economic and trade frictions between the two largest economies. This paper aims to analyze the economic impacts of the trade war effects using advanced econometric techniques. Our empirical study employs panel data analysis combined with a factor model, inspired by the methodologies of Hsiao, Ching and Wan (2012) and Bai, Li and Ouyang (2014), to construct trade patterns for both China and the US. By using annual trade data from multiple countries as a control group, we construct counterfactual results for China's and the US's imports, exports, and trade balance, respectively. Under a nonstationary setting, the counterfactual results indicate a significant decline in China's exports and a notable reduction in its trade surplus with the US post-2018. Meanwhile, US imports from China decreased, aligning with the trade war's goal of reducing the trade deficit, while US exports to China unexpectedly increased, possibly influenced by the Phase One trade agreement. We also perform a dynamic permutation test on treatment effects over time, which ensures the rigor and significance of our analysis, reinforcing the reliability of the estimated effects. Finally, we conduct an empirical comparative analysis with alternative methods to demonstrate that our chosen approach is particularly well-suited to the context of this study.

1. Introduction

In March 2018, President Trump signed a presidential memorandum based on the results of the "Section 301 Investigation", planning to impose large-scale tariffs on goods imported from China and to restrict Chinese companies from investing in and acquiring the US businesses. Over the following two years, the Trump administration continuously imposed additional tariffs, escalating economic and trade frictions between the US and China. In July and August 2018, the US government imposed a 25% tariff on $50 billion worth of Chinese imports in two batches. In response, China implemented equivalent measures of the same scale, targeting American products. By September 2018, the US imposed a 10% tariff on $200 billion worth of Chinese goods. As a response, China levied tariffs on $60 billion worth of the US goods. Over time, the US reneged on its commitments and continued to apply maximum pressure, escalating the trade war by imposing tariffs on approximately $370 billion worth of Chinese goods. After President Biden took office in January 2021, the US further escalated tensions, launching the so-called "strategic competition with China" through measures such as tariffs, export controls, and industrial subsidies. The motivations behind these trade sanctions are multifaceted. First, the US sought to reduce its significant trade deficit with China. Second, it criticized China for not providing fair and mutual market access to American companies. Finally, accusations of intellectual property theft by China served as a major catalyst for initiating the trade war.

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While this study does not aim to explore the entrenched causes of the trade war, its objective is to analyze the effects of this conflict on both countries within the context of global economic integration. The trade war between the US and China – given the scale of the tariffs and the size of the economies involved – has had, and may continue to have, significant impacts on the trade formats of both nations. This raises several critical questions: "What if" the trade war had never occurred? How would China's export scale have evolved? What would have been the scale of the US imports? Would these changes have had positive, negative, or neutral effects on the two economies? To answer these questions, we employ causal inference techniques that help identify the causal relationships between variables by comparing observed outcomes under conditions where the intervention did not occur.

The literature on causal inference in trade war studies spans various methodological approaches, with notable reliance on techniques like the difference-in-differences (DiD) method and the synthetic control method (SCM). The DiD estimates causal effects by comparing changes in outcomes between the treatment and control groups, adjusting for time-varying confounders, while the SCM creates a synthetic control by weighting control units to construct a counterfactual for the treated unit. Both methods, which fall under the broader category of quasi-experimental designs, are effective for isolating causal effects under specific assumptions. However, these methods can be limited when dealing with nonstationary time series data. To address these challenges, this study draws on the econometric frameworks introduced by Hsiao et al. (2012) (HCW) for stationary time series and extended by Bai et al. (2014) (BLO) to nonstationary scenarios, termed as panel data analysis (PDA) approach, which uses the structure of panel data to model complex dynamics and generates counterfactual scenarios. These methods are particularly well-suited for capturing the evolving impacts of the trade war.

By using the HCW and BLO methods, this study enhances causal inference in the context of trade wars, offering a more dynamic and robust analysis compared to traditional approaches. Our analysis contributes to the literature by introducing advanced econometric models that capture complex patterns from a causal inference perspective. Unlike previous studies, which predominantly report negative effects for both countries, our findings reveal mixed effects on trade flows between the US and China. We also perform a dynamic permutation test to assess the significance of treatment effects over time, rather than relying solely on the average treatment effect.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the effects of the trade war and causal inference studies, particularly those utilizing panel data analysis. Section 3 outlines the econometric framework employed to estimate counterfactual outcomes. Section 4 presents an empirical study applying the econometric methods introduced in Section 3 to analyze the trade war's impact on global and bilateral trade patterns between the US and China. This section also conducts a hypothesis test to verify the significance of the treatment effects. Finally, Section 5 concludes the paper.

2. Literature review

The literature on the China–US trade war employs a variety of methodologies, reflecting the diverse perspectives on its economic impacts. While some studies apply causal inference techniques to isolate the effects of the trade war, others focus on descriptive analyses, case studies, or structural models. The trade war has generated significant economic consequences, prompting researchers to explore its effects using a range of methods. Among the most common are the SCM, DiD, and computable general equilibrium (CGE) models. For instance, Fajgelbaum and Khandelwal (2022) found that while the trade war initially reduces the US trade deficit and increases China's trade surplus in short run, it exacerbates the trade deficit in the US and diminishes the trade surplus in China in the long run. In addition to this, Li et al. (2018) examined the impacts of varying tariff levels, concluding that trade wars generally harm most countries, particularly in terms of GDP and manufacturing employment, though they can benefit welfare and trade. However, the study primarily discusses potential outcomes rather than empirically observed effects. Similarly, Goulard (2020) assessed the trade war's impact on the EU, noting short-term benefits from trade diversions but warning of significant risks to global economic stability. Their analysis highlights how the China–US trade conflict could bring short-term trade advantages to the EU, yet the broader implications remain threatening for global stability and growth. Further research has focused on specific sectors, such as (Qiu et al., 2019), exploring the impact on international feed grain futures markets and China's pork market using Granger causality and the DCC-GARCH model. Their findings indicate that the trade war significantly increased volatility in Chinese pork prices. On a more macroeconomic scale, Steinbock (2018) contributed to the discussion on the potential for global economic decoupling and the risks tied to the US's foreign policy, although their study was limited by data and methodological constraints. The CGE model has been widely used to quantify trade war impacts, as demonstrated by studies such as Fajgelbaum and Khandelwal (2022), Li et al. (2018), and Cui et al. (2018). Finally, Fan et al. (2022) applied the DiD method to analyze how tariff trade barriers affect the operational performance of domestic firms, emphasizing the relationship between geopolitical uncertainty and firm performance. While the DiD method effectively controls for time-invariant unobserved heterogeneity and is relatively straightforward to implement, it assumes parallel trends in the absence of treatment, a limitation highlighted by Hsiao et al. (2012), noting that this assumption may not capture dynamic effects over time.

Some studies focus on the evolving relationship between China and the US over time, offering valuable insights to enhance the understanding of our analytical results. For example, Itakura (2020) constructed three scenarios for the period 2011–2035 using a modified model incorporating global value chains. They analyzed the effects of US tariff increases on imports from China across various goods categories. Expanding on this, Chong and Li (2019) argued that the economic impacts on China remain manageable even under worst-case scenarios. They also highlighted fundamental conflicts that could lead to prolonged economic tensions between the two countries. Similarly, Jiao et al. (2024) focused on Chinese exporters, finding that free-on-board prices of Chinese exports remained stable after accounting for firm-specific fixed effects. Although exports to the US decreased significantly, there was a moderate increase in exports to the EU, and sales within China or to other international markets remained largely unaffected.

Further, Hanson (2020) analyzed the direct correlation between tariffs and US prices, noting a nearly one-for-one impact. However, they concluded that these tariffs are unlikely to significantly affect manufacturing employment in the US, and not all US imports were subject to them. In a broader context, Liu and Woo (2018) recommended that China should enhance trade and investment reciprocity with other developed economies, while advising the US to distinguish between strategic and economic competition. This approach could foster long-term mutual benefits instead of immediate zero-sum outcomes. Other researchers have examined trade impacts through different theoretical aspects. For example, Qiu et al. (2019) explored various trade theories, including imperfect competition, increasing returns, terms of trade, and distributional effects, to offer a comprehensive understanding of the trade war's implications. Meanwhile, Kapustina et al. (2020) provided a detailed timeline of trade war milestones, emphasizing the political dimensions alongside economic consequences. However, our study focuses exclusively on the economic impacts, leaving political considerations outside its scope. Finally, Teimouri and Raeissadat (2019) investigated the trade war's side effects on countries within the Association of Southeast Asian Nations (ASEAN). Their findings indicate that China has a larger export share and deeper influence in poorer ASEAN countries compared to the US. Moreover, they noted that US tariffs have had minimal impact on ASEAN economies.

Clearly, the existing literature has laid a solid foundation for understanding the background and reasons behind the trade war's effects on national and global economies. As expected, many studies highlight negative outcomes from various perspectives. However, some fall short in offering sophisticated econometric models capable of capturing the intricate patterns underlying these impacts. To address this gap, we adopt the PDA method based on the factor model for panel data proposed by Hsiao et al. (2012), which has been successfully employed by many studies such as Bai et al. (2014), Ouyang and Peng (2015), and Ke and Hsiao (2022), and further extended by Bai et al. (2014) and Li and Sonnier (2022). Building on this foundation, we enhance the methodology by integrating generalized factor models developed by Bai et al. (2014), which extends the basic factor model to account for more complex data structures and interactions. Additionally, we incorporate the advancements proposed by Li and Sonnier (2022) for scenarios involving a single treated unit and a fixed number of control units with long panels. Using the projection theory, their approach demonstrates that modified synthetic control estimates and unconstrained estimators under HCW method are asymptotically distributed. By applying this advanced statistical framework, our study aims to provide a clearer and more detailed understanding of the trade war's impacts on China and the US. This contribution is expected to address existing methodological limitations in the literature and offer valuable insights into the economic implications of the trade war.

3. Econometric framework

In this section, we outline the econometric framework employed to estimate the effects of the trade war. While the observed impacts on the economies of China and the US are well-documented, the hypothetical scenario in the absence of the trade war remains unknown. To address this, constructing reliable counterfactuals is essential, as these represent the economic outcomes that would have occurred without the intervention. Several methods for counterfactual construction have been proposed in Section 2, each built upon distinct sets of assumptions (Abadie et al., 2010; Abadie & Gardeazabal, 2003; Hsiao et al., 2012; Li & Sonnier, 2022; Ouyang & Peng, 2015). In this study, we adopt the HCW approach, which utilizes observed outcomes from a control group to estimate counterfactuals, along with insights from BLO (2014) to refine the estimation. This method is particularly suitable for our analysis as it accounts for unobserved heterogeneity influencing trade dynamics, ensuring a robust framework for evaluating the trade war's causal impacts.

We consider an outcome of interest denoted by Y_{it} for unit $1 \le i \le N$ at time $1 \le t \le T$. A single treated unit receives an intervention starting at time T_0, while control units remain unaffected throughout the study period. The intervention[1] is indicated by D_{it}, where $D_{it} = 1$ signifies that unit i receives the intervention at time t, and $D_{it} = 0$ otherwise. A single treated unit receives an intervention starting at time t depending on the historical sequence of treatment indicators preceding t. By adopting the notations from (Robbins et al., 2004) and Boruvka et al. (2018), the potential outcomes influenced by prior treatment applications are defined as follows. Let $Y_{it}(1)$ and $Y_{it}(0)$ represent the potential outcomes for unit i if it were treated or not treated, respectively, from time T_0 onward:

$$Y_{it}(1) = Y_{it}(\underbrace{0\cdots 0}_{T_0}, \underbrace{1\cdots 1}_{T-T_0}) \text{ and } \quad Y_{it}(0) = Y_{it}(\underbrace{0\cdots 0}_{T_0}, \underbrace{0\cdots 0}_{T-T_0}).$$

Following the framework of HCW,[2] the first unit receives treatment starting at time T_0, such that $Y_{1t} = Y_{1t}(1)$ for $t = T_0 + 1, \ldots, T$, while the remaining units remain untreated, $Y_{it} = Y_{it}(0)$ for $i = 2, \ldots, N$ and $t = 1, \ldots, T$.

The treatment effect for the unique treated unit, $i = 1$, over time t from $T_0 + 1$ to T is defined as:

$$\tau_t = Y_{1t}(1) - Y_{1t}(0),$$

and its average treatment effect (ATE) is given by $\tau = \mathrm{E}\left[Y_{1t}(1) - Y_{1t}(0)\right]$. In practice, both τ_t and τ are estimable only if $Y_{1t}(0)$ would be observable, denoted by $\hat{\tau}_t$ and $\hat{\tau}$, respectively. Specifically, $\hat{\tau}$ can be estimated over the entire policy evaluation period $[T_0+1, T]$ as $\hat{\tau} = \sum_{t=T_0+1}^{T} \hat{\tau}_t/(T - T_0)$ if $Y_{1t}(0)$ would be observable. The primary challenge lies in the fact that $Y_{1t}(0)$ is generally unobservable and may exhibit nonstationary behavior, so that it complicates its estimation.

1 In this paper, we use the terms intervention, exposure, and treatment interchangeably.

2 Throughout the paper, the method described by Hsiao et al. (2012) is equivalently referred to as the "HCW" or "PDA" or "factor model".

To estimate the counterfactual outcome $Y_{1t}(0)$ for the treated unit after treatment, we employ the HCW method, utilizing outcomes from the control group. Specifically, we assume that the N cross-sectional units, denoted by $\mathbf{Y}_t = (Y_{1t}, \ldots, Y_{Nt})^\top$, are generated from the following factor model:

$$\mathbf{Y}_t = \mathbf{a} + \mathbf{B}\mathbf{f}_t + \mathbf{u}_t,$$

where $\mathbf{a}$ are $N \times 1$ fixed unit effects, $\mathbf{f}_t$ is an $r \times 1$ vector of common factors, $\mathbf{B}$ is an $N \times r$ factor loadings, and $\mathbf{u}_t$ are $N \times 1$ idiosyncratic error term with $\mathrm{E}(\mathbf{u}_t|\mathbf{a}, \mathbf{f}_t) = \mathbf{0}$. Then, under certain assumptions (see Assumption 5 in Bai et al., 2014), it follows from Proposition 2.1 in Bai et al. (2014)[3] that the model for the treated outcome Y_{1t} can be simplified to:

$$Y_{1t} = \gamma_0 + \gamma_1^\top \tilde{\mathbf{Y}}_t + e_{1t},$$

where $\tilde{\mathbf{Y}}_t = (Y_{2t}, \ldots, Y_{Nt})^\top$ denotes the outcomes of the control units.[4]

In the HCW method, the factor $\mathbf{f}_t$ was initially assumed to follow a strictly stationary process. However, in our empirical study, variables may be nonstationary and endogenous. To address these difficulties, Bai et al. (2014) and Li (2020) showed that, under regularity conditions, the presence of mildly endogenous regressors does not compromise the consistency of the ordinary least squares (OLS) estimators $\hat{\gamma}_0$ and $\hat{\gamma}_1$, and, as argued by Cai and Wang (2014), the OLS estimate of the coefficient for a nonstationary regressor enjoys a super-consistent convergence rate. Consequently, the counterfactual outcome $Y_{1t}(0)$ can be estimated by (1) as $\hat{Y}_{1t}(0) = \hat{\gamma}_0 + \hat{\gamma}_1^\top \tilde{\mathbf{Y}}_t$ for $t \geq T_0 + 1$.

The steps for estimating counterfactual results are summarized as follows:

1. **Estimation of Unobserved Factors**: We assume that the control units are unaffected by the treatment, allowing their observed outcomes to serve as a basis for estimating the latent factors $\mathbf{f}_t$. In our empirical analysis, these latent factors are approximated using the outcomes of the control group. Specifically, from (1), we do not estimate $\mathbf{f}_t$ directly but instead run the regression model specified in (1) for the pre-treatment period ($1 \leq t \leq T_0$) to obtain $\hat{\gamma}_0$ and $\hat{\gamma}_1$.
2. **Predicting Counterfactuals**: The counterfactual outcomes for the treated unit, assuming the absence of treatment, are predicted using the estimated coefficients. The counterfactual outcome at time t is computed as $\hat{Y}_{1t}(0) = \hat{\gamma}_0 + \hat{\gamma}_1^\top \tilde{\mathbf{Y}}_t$ for $t \geq T_0 + 1$.
3. **Calculation of Treatment Effects**: The treatment effect for the treated unit at each time t is calculated as the difference between the observed outcomes and the predicted counterfactual outcomes as $\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}(0)$.

4. Empirical study on evaluating trade war effects

The China–US trade war, which began in 2018, represents a pivotal moment in international economics, fundamentally altering trade dynamics between two of the world's largest economies. This empirical study seeks to assess the ongoing impacts of the trade war on China and the US using a causal analysis framework. Given the complexity and worldwide effects of this event, accurate evaluation requires a nuanced approach, using advanced econometric techniques to effectively capture these shifts.

A key requirement for applying the HCW method is the careful selection of a control group. For example, the control group should share economic characteristics with the treated unit, China for instance, such as being export-oriented, while remaining unaffected by the trade war. However, the interconnected nature of the global economy poses challenges in constructing a perfectly matched synthetic control group, as no country or group can fully replicate China's trade dynamics. Despite this inherent limitation, this study strives to construct credible comparisons that highlight the multifaceted effects of the China–US trade war while mitigating potential biases from these assumptions.

The evaluation process is divided into three main parts. First, we describe the dataset, detailing its characteristics and presenting results from the augmented Dickey–Fuller (ADF) tests applied to each country's trade data. Second, we analyze the trade war's effects from two perspectives: a "global view" and a "China–US trade view", to examine its impact on both nations.[5]

4.1. Data description

Although the China–US trade war was officially initiated in March 2018, its economic effects were already apparent by January of that year. Therefore, this study sets 2018 as the intervention point for analysis. Using nominal yearly trade data for all product categories from World Integrated Trade Solution (WITS) in World Bank at https://wits.worldbank.org/, it examines trade patterns and how the effects of the trade war have evolved over time. This study evaluates the trade war's ongoing effects on the trade performance of both China and the US. Note that the starting point for available data differs across scenarios.

It is well known that the selection of an appropriate control group is crucial for obtaining reliable counterfactual results. LASSO (the least absolute shrinkage and selection) is a widely used method for selecting control units as in Bloniarz et al. (2016)

[3] Refer to Bai et al. (2014) for further details.

[4] In practical applications, the model in (1) can be extended to include a p-dimensional vector of exogenous covariates, $\mathbf{X}_t$, as follows:

$$Y_{1t} = \gamma_0 + \gamma_1^\top \tilde{\mathbf{Y}}_t + \gamma_2^\top \mathbf{X}_t + e_{2t}.$$

However, in this study, we do not include such covariates in our analysis.

[5] Due to China and the US adopting different statistical standards for calculating trade imports and exports, the following analysis separates the data for China and the US.

and Shortreed and Ertefaie (2017), since it can effectively identify the most relevant units from a large pool of potential controls. In our analysis, we first apply LASSO to ensure statistical significance in the selection process. However, given that our N is not very large, we also emphasize economic relevance in our final selection. The units selected by LASSO largely align with our economically motivated choices. Additionally, we include certain trade partners based on specific economic considerations, as detailed in the following discussions.

4.1.1. Global perspective on China trade

For this part of the analysis, we use annual total export and import data[6] for China from 1988 to 2022.[7] The control group consists 17 countries, including South Korea, Japan, Australia, New Zealand, Thailand, Vietnam, Malaysia, Indonesia, Singapore, India, Germany, Italy, France, South Africa, Mexico, Brazil, and Argentina. These countries were selected to provide a robust benchmark for modeling China's trade performance, considering their economic characteristics and trade dynamics.

The selection of countries depends on economic similarities to China's export-oriented economy. Specifically, the control units were chosen based on the following criteria. First, the selected countries have historically exhibited strong export-driven growth, making them comparable to China in terms of trade dynamics. Second, many of these economies have actively pursued policies aimed at expanding global trade, similar to China's trade strategy. Third, the control group includes major Asian economies that share regional trade linkages with China, as well as key non-Asian export-driven economies that provide a broader perspective for comparison. A similar selection method is applied in the case of China's bilateral trade.

The analysis covers 18 countries, with China as the treated unit and the remaining 17 as the control group. The treatment is assumed to begin in year $T_0 = 30$ (2018), and the total duration of the study spans $T = 35$ years of time. The factor model introduced in Section 3 is applied to construct counterfactual outcomes for China's total exports, imports, and trade balance. This approach enables us to quantify the trade war's overall impact on China's trade performance.

4.1.2. Global perspective on US trade

For the analysis of the US international trade, we use annual total export and import data spanning from 1988 to 2022. The control group comprises 23 countries: South Korea, Japan, Australia, Thailand, Vietnam, Malaysia, Indonesia, Singapore, India, Germany, Italy, France, Mexico, Brazil, the United Kingdom, the Netherlands, Canada, Spain, Turkey, Poland, Switzerland, the United Arab Emirates, and Austria.

The control group selection for the US differs from that of China due to its import-driven economic structure and its significant role as a high-tech exporter. The control group was selected based on the following factors: import-oriented economics, presence of high-tech exporters, such as the UK and Netherland, and has diverse trade networks that the US has historically maintained strong trade relationships with a broad range of partners, particularly in Europe and North America. This tailored selection ensures that the control group reflects both the US's role as a major importer and its high-tech export patterns, making it a suitable benchmark for assessing the impact of the trade war on US trade performance. A similar selection method is applied in the case of the US bilateral trade.

To assess the impact, we apply the factor model to synthesize potential outcomes for the US's total exports and imports as if they were unaffected by the trade war, thus evaluating the general impact of the trade war on US international trade. For this scenario, the measurements include 24 countries in total with one unit in the treatment group and 23 in the control group, spanning a total duration of $T = 35$ time units.

4.1.3. Bilateral trade of China and the US: China's perspective

The second part of the analysis examines the trade relationship between China and the US. Using trade data with other countries, we estimate potential trade outcomes and compare the impact of the trade war on both nations.

From China's perspective, the dataset spans from 1992 to 2022.[8] Here, the treated unit is China's total trade with the US, while the control group consists of 20 of China's major trade partners: South Korea, Japan, Australia, New Zealand, Thailand, Malaysia, Indonesia, Singapore, India, Vietnam, Germany, Italy, France, South Africa, Mexico, Brazil, Canada, Netherlands, Russian Federation, and the UK. These countries represent a diverse group of China's most significant trade partners, with several sharing similar export-driven trade strategies. It ensures a representative and comprehensive view of potential trade outcomes between China and the US.

The analysis encompasses a total of 21 countries, with one treated unit and 20 control units, spanning a total duration of $T = 31$ time units, and $T_0 = 26$.

[6] Data Source: World Integrated Trade Solution

[7] This study utilizes the most recent and comprehensive trade data available at the time of the research.

[8] This represents the longest available time frame from China's official sources.

Table 1
Augmented Dickey–Fuller test results for exports data.

Variable	Log levels			Log-first differences		
	None	Drift	Trend	None	Drift	Trend
China	0.9999	0.9972	0.4785	0.0082***	0.0001***	0.0001***
US	0.9970	0.7434	0.4785	0.0000***	0.0000***	0.0000***
South Korea	1.0000	0.0162	0.4412	0.0001***	0.0000***	0.0068***
Japan	0.9977	0.0000***	0.0021***	0.0000***	0.0000***	0.0000***
Australia	0.9999	0.2123	0.0381	0.0001***	0.0000***	0.0001***
New Zealand	0.9544	0.5475	0.5480	0.0270	0.1953	0.3935
Thailand	1.0000	0.0000***	0.0057***	0.0059***	0.0000***	0.0000***
Vietnam	1.0000	0.1370	0.0000***	0.0831	0.0085***	0.0078***
Malaysia	1.0000	0.0000***	0.0058***	0.0000***	0.0000***	0.0345
Indonesia	1.0000	0.0353	0.8320	0.0016***	0.0005***	0.0994
Singapore	0.9999	0.0000***	0.0008***	0.0000***	0.0001***	0.0001***
India	1.0000	0.0033***	0.5494	0.0152	0.0001***	0.0000***
Germany	1.0000	0.0000***	0.0765	0.0385	0.0003***	0.5399
Italy	1.0000	0.0004***	0.1203	0.0005***	0.0079***	0.0064***
France	1.0000	0.0000***	0.1554	0.0148	0.0032***	0.0029***
South Africa	1.0000	0.0399	0.9879	0.0974	0.3300	0.0004***
Mexico	0.9975	0.0001***	0.0138	0.0000	0.0000***	0.0000***
Brazil	1.0000	0.0156	0.7466	0.0156	0.0000***	0.1284
Argentina	1.0000	0.0000***	0.0311***	0.0001***	0.0004***	0.0004***
United Kingdom	0.9994	0.0029***	0.3826	0.0002***	0.0004***	0.0893
Netherlands	0.9999	0.0023***	0.8149	0.0013***	0.0024***	0.0022***
Canada	0.9775	0.5605	0.1878	0.0000***	0.0859	0.7493
Spain	0.9999	0.1742	0.5861	0.0475	0.1427	0.1787
Turkey	1.0000	0.0039***	0.8538	0.0162	0.0685	0.1344
Poland	1.0000	0.0010***	0.3930	0.0467	0.1418	0.0852
Switzerland	1.0000	0.3240	0.5297	0.0548	0.0741	0.6828
United Arab Emirates	0.9991	0.0051***	0.6495	0.0001***	0.0078***	0.0941
Austria	1.0000	0.0016***	0.5206	0.0762	0.1195	0.2267

Note: This table provides detailed p-values of the augmented Dickey–Fuller (ADF)tests for both log levels and log-first differences on each country's export data under different assumptions. "None" means no drift or trend; "Drift" indicates the test specification allows for a drift; and "Trend" implies the test includes a time trend. P-values marked with *** indicate significance at the 1% level, implying the rejection of the null hypothesis of non-stationarity.

4.1.4. Bilateral trade of China and the US: US perspective

From the US perspective, the analysis focuses on US trade with China as the treated unit, with data spanning 1991 to 2022. The control group consists of 18 key trade partners: South Korea, Australia, Japan, Thailand, Malaysia, Singapore, India, Germany, Italy, New Zealand, France, South Africa, Mexico, Brazil, Canada, the United Kingdom, Switzerland, and Israel. The selection is justified by the long-standing trade relationships of countries like Canada, Germany, and the UK with the US, making them suitable control units.

The composition of the control group reflects the distinct trade relationships and economic dynamics of the US compared to China. For this scenario, the measurements include 19 countries with one unit in the treatment group and 18 in the control group, $T_0 = 27$, and the total duration $T = 32$.

4.2. Unit root tests

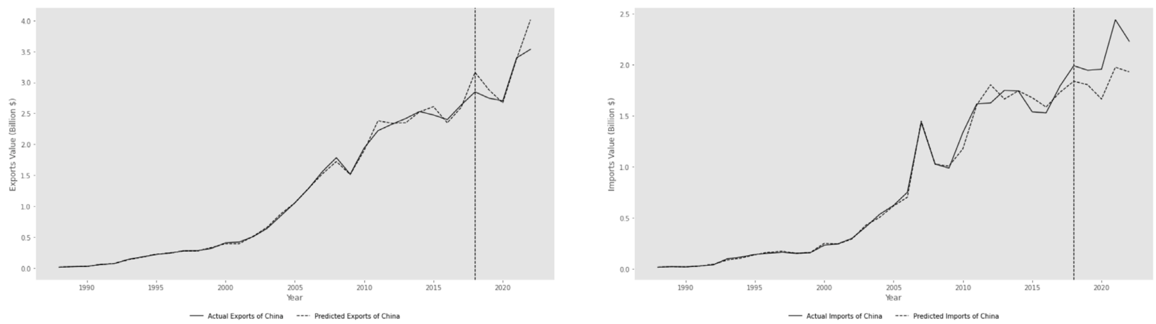
In this section, we test for the presence of unit roots in the trade data to examine the stationarity of the series. The following presents the non-stationarity test results for total exports data. For more additional details, please refer to Appendix. The key results of the tests are summarized in Tables 1.

Table 1 presents the results of the Augmented Dickey–Fuller (ADF) test for export data across all countries. At log levels, most countries are nonstationary, except for a few like Japan, Thailand, and Malaysia, when drift or trend is included. After first differencing, most countries achieve stationarity, with significant p-values across all specifications, particularly for China, the US, and South Korea. However, a few countries, like Indonesia and Switzerland, still exhibit non-stationarity under certain conditions.

Based on the ADF test results presented in the tables, it is evident that not all data series are stationary. This highlights the need for the BLO method, which accounts for the non-stationarity of the data and allows for the construction of counterfactual results under I(1) processes.

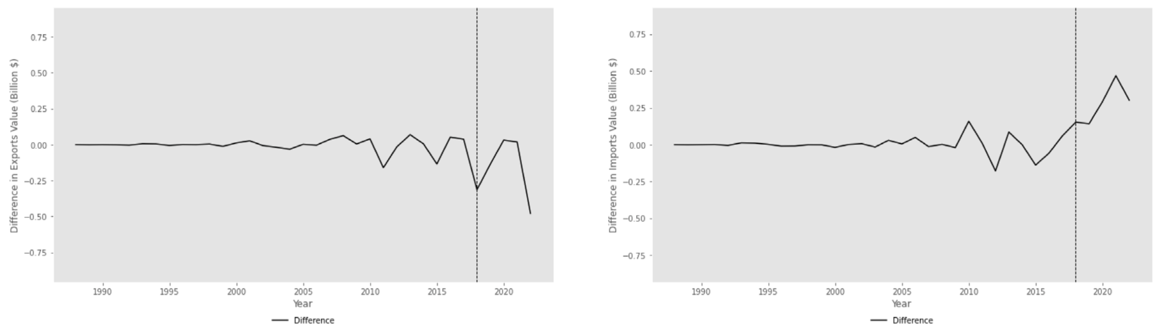
4.3. Empirical results

In this section, the first part presents a global perspective, discussing the total imports and exports of China and the US and the second part analyzes the trade patterns of each country individually, with a focus on the changes brought about by the trade war.



(a) China's total exports. (b) China's total imports.

Fig. 1. China's total exports (left panel) and imports (right panel): the true value in solid line and the predicted value in dashed line, from 1998 to 2022.



(a) Treatment effect of China total exports. (b) Treatment effect of China total imports.

Fig. 2. The difference between actual and predicted total exports (left panel) and imports (right panel) of China from 1988 to 2022.

4.3.1. Global trade of China and the US

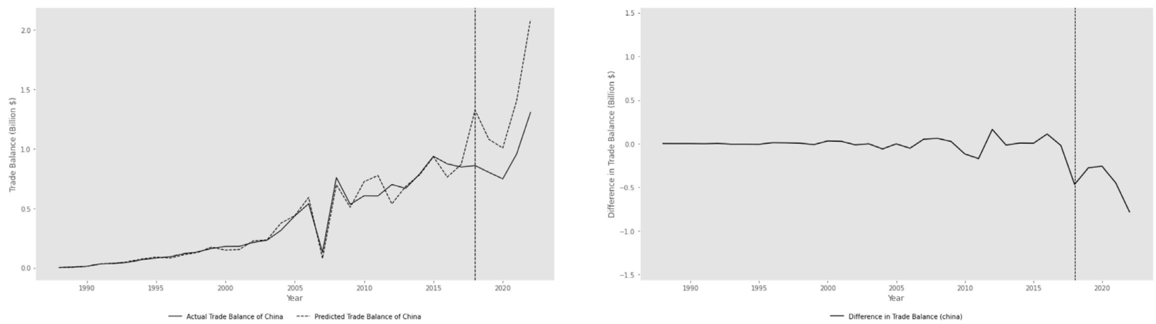
A. Global Perspective on China Trade

Fig. 1 presents the predicted results for China's total exports and imports. Fig. 2 displays the difference between actual and predicted total exports of China from 1988 to 2022. Two key observations can be made: prior to 2018, the differences are small and stable, indicating the model's accuracy in predicting China's export pattern. After 2018, following the onset of the trade war, a noticeable divergence occurs, with actual exports falling below the predicted values. During 2019–2020, the gap between actual and predicted exports narrows significantly, suggesting a return to normal export levels. This indicates that despite the trade war, China managed to stabilize its exports, possibly by finding alternative markets or adjusting trade strategies to mitigate the impact of the trade war. Since 2021, the difference slightly widens again, which may be attributed to factors such as changes in global demand or adaptations by Chinese exporters.

Fig. 3 displays China's trade balance, while Fig. 3(a) compares actual and predicted trade balances. A clear departure begins in 2017 and becomes more pronounced in 2018, indicating a shrinking trade balance due to reduced exports. One possible contributing factor could be the Covid-19 outbreak. Fig. 3(b) highlights the decline and fluctuations in China's trade balance from 2018 to 2022, suggesting the impact of US sanctions on Chinese exports. The difference widens after 2020 and does not return to the potential level until 2022, indicating the continued impact of the trade conflict on China's trade balance as a whole.

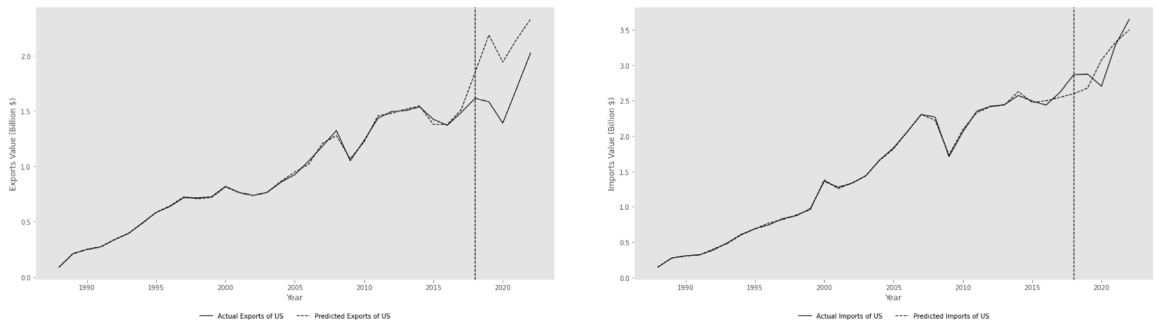
The reduction in China's trade balance can be attributed to several factors. However, imports initially show stability, with actual imports exceeding predicted values. This may be due to China diversifying its import sources, reducing reliance on US goods, and increasing imports from other countries. Despite the shocks to China's exports, which were still under control, this helped mitigate the trade war's impact on total import volumes.

Overall, the trade war had a direct and immediate negative effect on China's total exports starting in 2018, while imports were less affected. The expected reduction in exports due to US sanctions is evident — In 2018, President Trump imposed tariffs on $34



(a) Trade balances of China. (b) Treatment effect of China trade balance.

Fig. 3. Trade Balance of China from 1998 to 2021. The left panel is for trade balance of China: the true value in the solid line and predicted value in the dashed line, and the right panel is for the treatment effect.



(a) US's total exports. (b) US total imports.

Fig. 4. US's total exports (left panel) and imports (right panel): the true value in solid line and the predicted value in dashed line, from 1998 to 2022.

billion worth of Chinese goods, with additional tariffs on $200 billion of goods later introduced. However, China's import strategies effectively mitigated the adverse effects, resulting in unexpectedly increased import volumes from the global market.

B. Global Perspective on US Trade

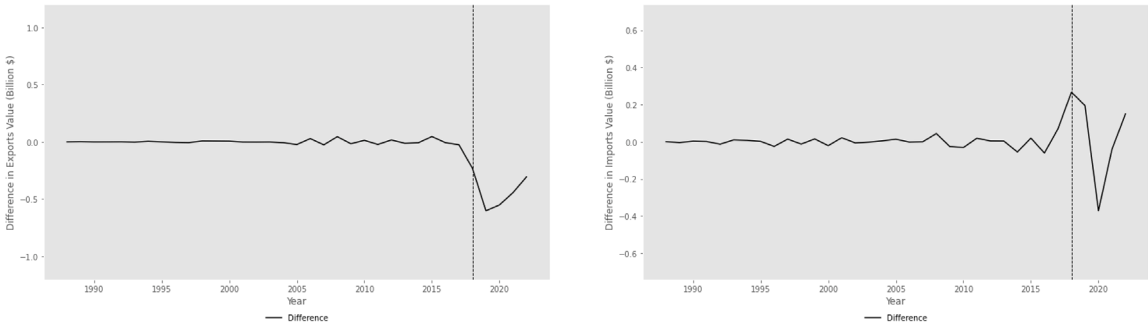
Fig. 4 depicts the predicted trade volume for the US total exports and imports. In Fig. 4(a), the actual exports appear to diverge downward from the predicted values, suggesting a possible impact of the trade war on US export behavior. Compared to China's exports, this divergence is more pronounced for the US in terms of scale rather than volume. However, in terms of imports, as shown in Fig. 4(b), the actual values do not significantly deviate from the estimated results, indicating that imports may not have been substantially influenced by the trade war after 2018.

In Fig. 5(a), there is a slight drop in exports post-2018, likely due to China's retaliatory tariffs, followed by a direct increase to the predicted levels after 2019, though still below the potential level. The US exports fell for a number of reasons. One was China's imposition of retaliatory tariffs in response to President Trump putting duties on over $300 billion of Chinese exports. A second reason was the reduced competitiveness of American products, driven by higher input costs from Trump's tariffs, which mainly affected parts and components essential for businesses. According to Fig. 5(b), imports do not appear to be significantly affected by the trade war, exhibiting reasonable fluctuations while remaining slightly higher than the predicted imports overall. This indicates that the US generally maintained its global export and import levels despite the trade conflict.

Finally, Fig. 6 presents the predicted trade balance of the US, showing a higher predicted balance compared to the actual data from 2018 to 2019, suggesting that the trade war did not significantly reduce the US trade deficit. After 2020, the actual trade balance continues to decline, albeit at a slower rate, and does not converge with the predicted result. This indicates that the trade war had a limited effect overall. The treatment effect on the US trade balance does not appear to have had a significant impact on the US international market compared to its impact on China. Further details will be discussed in Section 4.3.2.

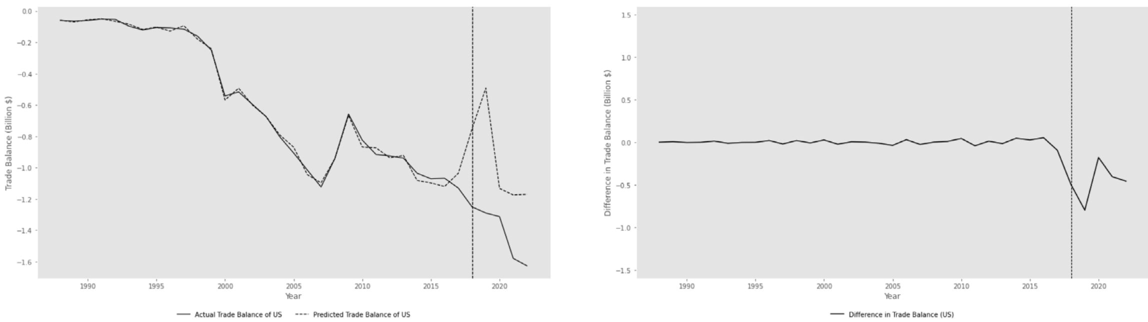
4.3.2. Bilateral trade of China and the US

In the second part of the analysis, we examine the trade between China and the US to capture the effects of the trade war on their trade dynamics. Discrepancies in trade data arise because China employs the general trade system (GTS) for both exports and imports, while the US primarily uses for imports but relies on domestic exports for goods produced within the US, excluding



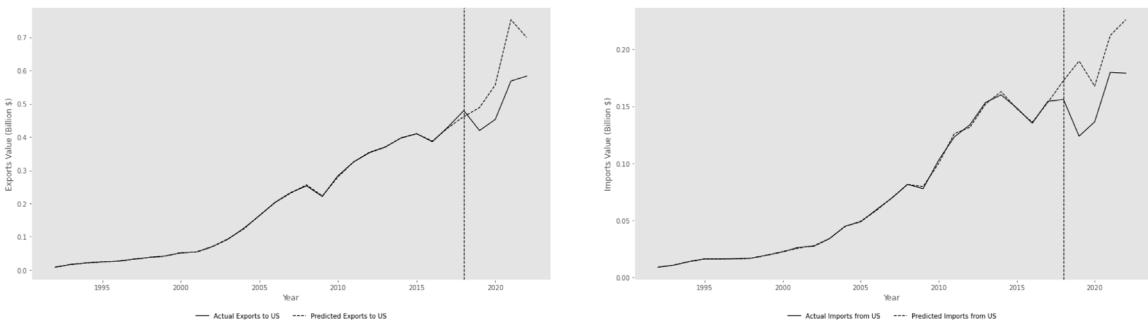
(a) Treatment effect of US's total exports. (b) Treatment effect of US total imports.

Fig. 5. The difference between actual and predicted total exports (left panel) and imports (right panel) of the US from 1988 to 2022.



(a) Trade balances of the US. (b) Treatment effect of the US trade balance.

Fig. 6. Trade Balance of the US from 1998 to 2022. The left panel is for trade balance of China: the true value in the solid line and predicted value in the dashed line, and the right panel is for the treatment effect.



(a) Predicted China exports to US (b) Predicted China imports from US

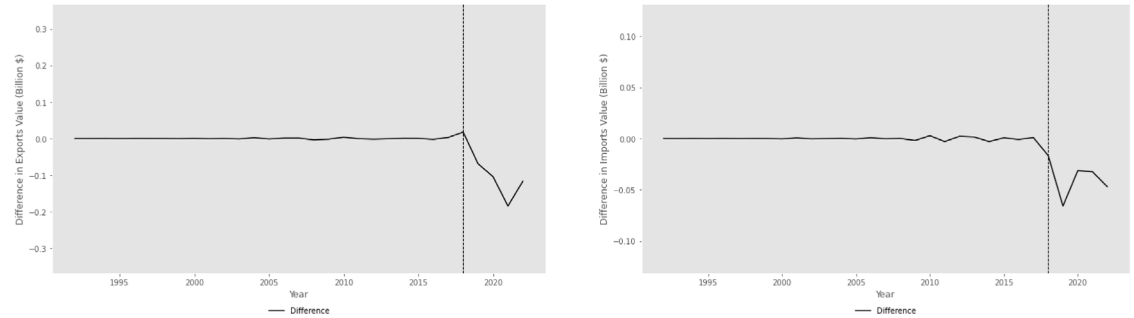
Fig. 7. Predicted results by factor model.

re-exports. Furthermore, differences in how administrative and processing zones are accounted for may contribute to inconsistencies in the data.

A. Bilateral Trade from China's Perspective

From China's perspective, three cases are analyzed as treated units: China's exports to the US, imports from the US, and the trade balance with the US. Fig. 7 presents the predicted results for China's exports to and imports from the US. Both exports and imports show a decline immediately after 2018, with imports experiencing a more significant drop due to China's retaliatory tariffs in response to US duties on Chinese exports.

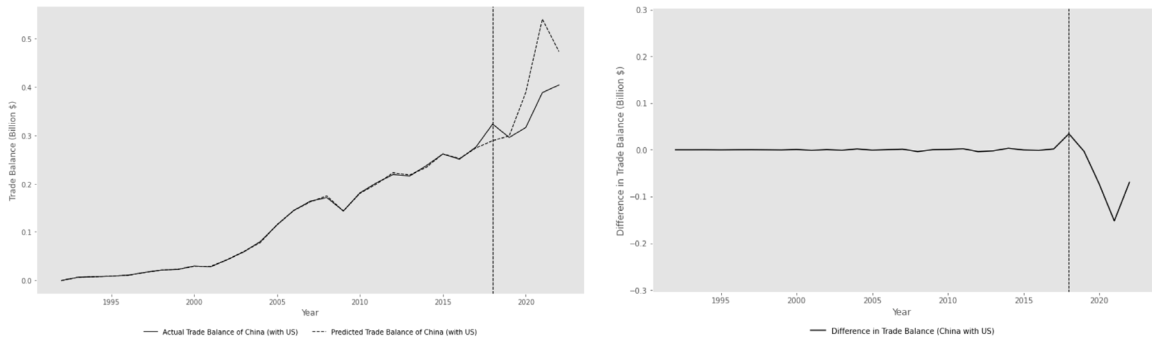
Fig. 8 shows the differences between the actual trade data and the predicted results, highlighting decreases in both exports and imports post-2018 as treatment effects, with imports declining more sharply. The difference in exports highlights the impact of US



(a) Treatment effects over time - China exports to US

(b) Treatment Effects over time - China imports from US

Fig. 8. Predicted results by factor model.



(a) Predicted Trade Balance of China with US

(b) Treatment Effects of China T.B. with US

Fig. 9. Predicted Results by Factor Model.

sanctions on China, which negatively affected China's exports. However, after 2020, there are signs of recovery. In contrast, the difference in imports from the US fluctuates significantly but still lags behind the potential level, emphasizing China's response to the US sanctions. These sanctions, imposed due to perceived "unfair trade practices", contributed to the widening US trade imbalance.

As we know, if the predicted results are higher than the actual data, it indicates that the trade war has negatively impacted China's trade surplus, and vice versa. Fig. 9 shows China's trade balance with the US, where the predicted result is higher than the actual trade balance, suggesting that US sanctions reduced China's trade balance with the US by over $150 millions. Despite this, China still maintained a trade surplus with the US, and the trade balance has shown signs of recovery after 2020.

Overall, from China's perspective, the trade war has led to a decline in both exports to and imports from the US, with a more significant drop in imports, highlighting China's strong reaction to US sanctions. This reflects China's strategic efforts to mitigate the effects of US tariffs, resulting in a substantial decrease in the trade surplus with the US.

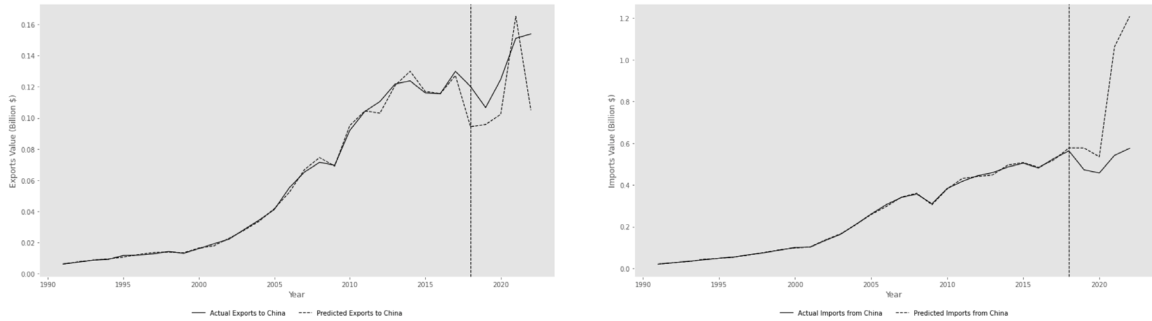
B. Bilateral Trade from the US Perspective

Next, we analyze the trade changes from the US perspective. Similarly, Fig. 10 presents the predicted results for US exports to and imports from China. In Fig. 10(a), we observe that actual US exports to China exceeded the predicted results in general. This is likely due to the 'Phase One Trade Agreement' signed in January 2020, in which China committed to significantly increasing its purchases of US goods and services over the next two years, leading to actual exports surpassing normal levels.

Fig. 11 combines the differences in US exports to and imports from China, revealing no significant impact on US exports. However, imports from China decreased, which aligns with the initial objectives of the trade war discussed in Section 4.3.1.

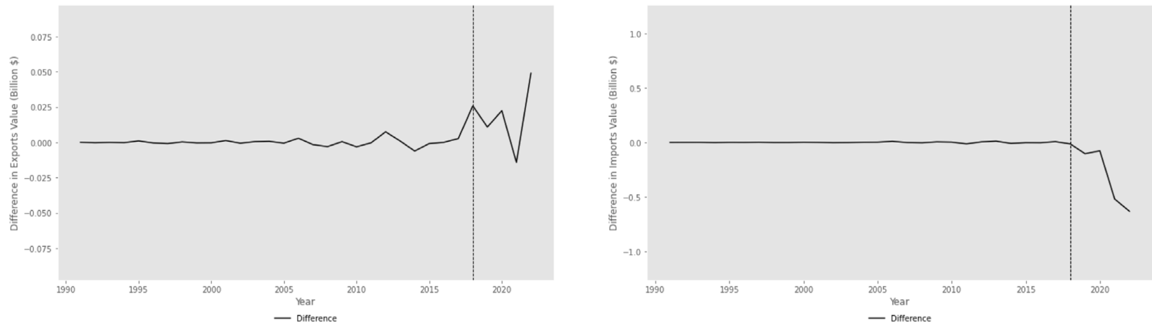
Fig. 12 shows the US trade balance with China. From Fig. 12(a), we observe that the actual trade balance is higher than the predicted one, indicating that the trade war increased the US trade balance with China. This aligns with the initial goal of reducing the trade deficit. The result supports a point made by Fajgelbaum and Khandelwal (2022), which suggests that the trade war reduces the US trade deficit while boosting China's trade surplus. However, in the long run, the trend may reverse.

Overall, from the US perspective, the trade war with China has had mixed effects on trade dynamics. While the trade war led to a decrease in US imports from China, contributing to the goal of reducing the trade deficit, the Phase One agreement resulted in higher-than-expected US exports to China, somewhat mitigating the overall positive impact on trade dynamics.



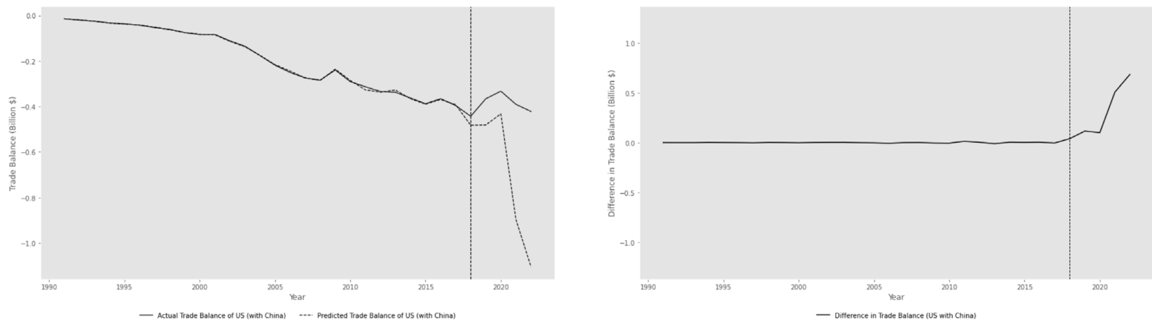
(a) Predicted US exports to China (b) Predicted US imports from China

Fig. 10. Predicted results by factor model.



(a) Treatment effects over Time - US exports to China (b) Treatment effects over time - US imports to China

Fig. 11. Predicted results by factor model.



(a) Predicted Trade Balance of US with China (b) Treatment Effects - US T.B. with China

Fig. 12. Predicted Results by Factor Model.

Building on the analysis, these results raise an important question: What is the mediation effect accompanying the trade war's impact? In other words, if China and the US reduce exports or imports from each other, which other countries or regions might influence their trade patterns? This can be explored in a future research.

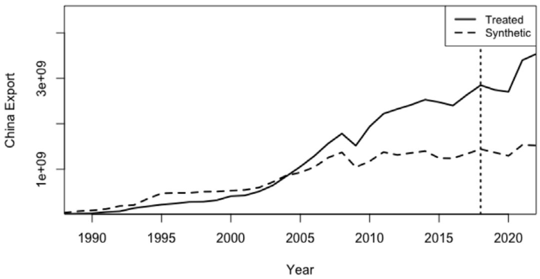
4.4. Hypothesis test

To assess whether the China–US trade war significantly impacted trade between the two countries, we apply a permutation test, also known as a placebo test, following the methods used in the papers by HCW and BLO. Since the trade war's effects evolve over time and are not consistently positive or negative, we use a time-varying permutation test to capture these dynamic changes instead

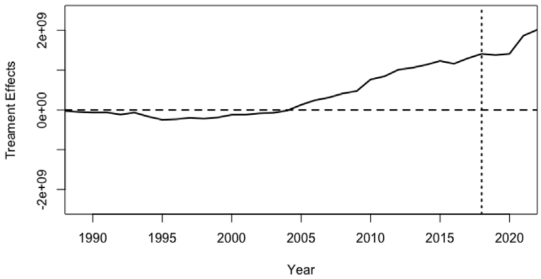
Table 2
Hypothesis test results on treatment effect over years.

Year	Country	Treatment effect (*p*-value)			
		Total export	Total import	Exports to	Imports from
2018	China	−0.1045 (0.000)	0.0798 (0.000)	0.0382 (0.000)	−0.1005 (0.000)
2019	China	−0.0480 (0.000)	0.0758 (0.000)	−0.1525 (0.000)	−0.4267 (0.000)
2020	China	0.0118 (0.000)	0.1611 (0.000)	−0.2069 (0.000)	−0.2070 (0.000)
2021	China	0.0055 (0.000)	0.2125 (0.000)	−0.2812 (0.000)	−0.1659 (0.000)
2022	China	−0.1273 (0.000)	0.1450 (0.000)	−0.1822 (0.000)	−0.2334 (0.000)
2018	US	−0.1339 (0.000)	0.0977 (0.000)	0.2415 (0.000)	−0.0246 (0.000)
2019	US	−0.3227 (0.000)	0.0702 (0.000)	0.1077 (0.000)	−0.1998 (0.000)
2020	US	−0.3342 (0.000)	−0.1287 (0.000)	0.1980 (0.000)	−0.1571 (0.000)
2021	US	−0.2317 (0.000)	−0.0120 (0.000)	−0.0896 (0.000)	−0.6738(0.000)
2022	US	−0.1409 (0.000)	0.0421 (0.000)	0.3824 (0.000)	−0.7421 (0.000)

Note: This table presents the estimated treatment effects and corresponding p-values of the trade war for each year from 2018 onward. All treatment effects are measured in billions and are statistically significant at the 1% level. "Exports to" and "Imports from" denote bilateral trade flows between China and the US.



(a) SCM results – China exports



(b) Treatment effects –China exports

Fig. 13. Differences between the SCM and real data.

of static tests. This test examines whether the observed deviations in trade data each year after 2018 are statistically significant compared to a counterfactual scenario in which the trade war did not occur. The hypotheses for each t are given by

$$H_0^t : \tau_{D,t} = 0 \quad \text{versus} \quad H_1^t : \tau_{D,t} \neq 0,$$

which tests if the China–US trade war did not have a significant impact on China's or the US's trade over time or not.

The test results are presented in Table 2, which show that all treatment effects are statistically significant at the 1% significance level. The results align with our earlier analysis, confirming the robustness of our findings. The permutation test consistently yields p-values below 0.05 for all years, indicating a significant impact of the trade war. Note that the treatment effect varies over time, mirroring the trends observed in our analysis. For instance, China's total exports experienced an initial decline in 2018–2019, a temporary recovery in 2020–2021, and a renewed downturn in 2022. These findings are consistent with the patterns discussed in the previous section and further reinforce the reliability of our analysis.[9]

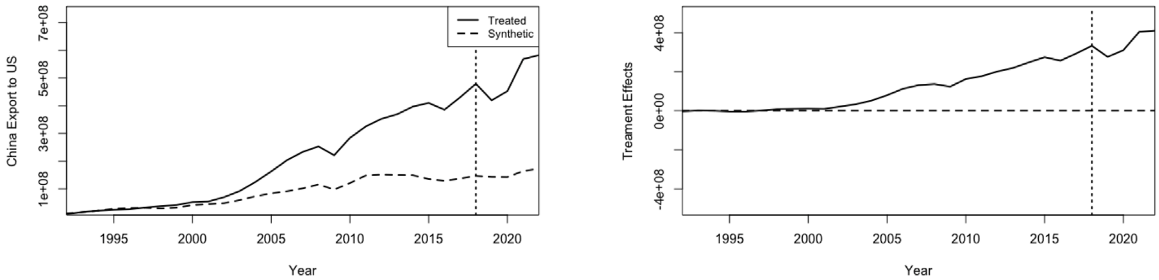
4.5. Comparison with other methods

The following section presents counterfactual results generated using two widely used methods (SCM and MSC), serving as benchmarks for comparison with the results from our primary approach.

4.5.1. Comparison with the SCM

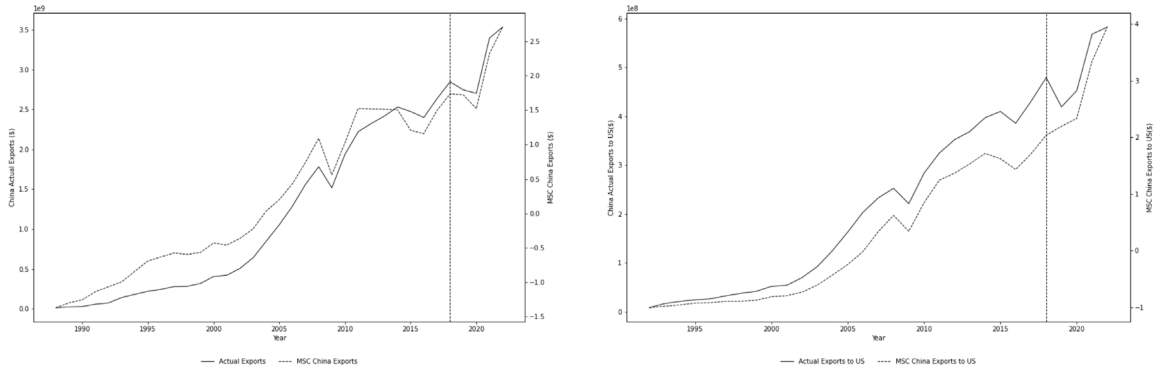
We first apply the SCM, introduced by Abadie et al. (2010) and Abadie and Gardeazabal (2003) to derive counterfactual outcomes. The SCM is widely used in comparative case studies and performs when there is a single treated unit with a long pre-treatment period and a stable donor pool. To keep the discussion concise, we present the results for China as a representative case. Figs. 13 and 14 show the SCM-based counterfactuals and estimated treatment effects for China's total exports and exports to the US.

[9] We sincerely appreciate the reviewer's valuable suggestions regarding the formal hypothesis testing for the significance of treatment effects. This insightful feedback has enabled us to enhance the rigor and comprehensiveness of our empirical analysis, leading to more robust and well-substantiated results.



(a) SCM results – China exports to US (b) Treatment effects –China exports to US

Fig. 14. Differences between the SCM and real data.



(a) MSC results – China exports (b) MSC results – China exports to US

Fig. 15. Differences between the MSC and real data.

A key issue is the substantial divergence between the synthetic and actual outcomes even before the trade war began, suggesting poor pre-treatment fit. Furthermore, SCM estimates imply positive treatment effects following the trade war – suggesting beneficial impacts – which contradict the widely documented disruptions caused by the conflict. These inconsistencies stem from SCM's limitations: it does not explicitly model dynamic trade patterns over time and relies on restrictive assumptions, including non-negative weights that sum to one. This convexity constraint can prevent accurate counterfactual construction, especially when the treated unit lies outside the convex hull of control units, as is likely the case here.

4.5.2. Comparison with the MSC

The MSC proposed by Li and Sonnier (2022) relaxes some of SCM's restrictions, including the sum-to-one requirement, and is designed for high-dimensional settings. However, it still enforces non-negative weights and relies on a subsampling procedure that requires a long time dimension to perform effectively, which are not met in our dataset.

As shown in Fig. 15, the MSC results for China's trade are notably inconsistent with the actual data: the synthetic series significantly underestimates trade levels prior to the trade war and continues to fall well below observed values throughout the treatment period. Although the gap narrows slightly after the onset of the trade war, the counterfactual remains implausibly low. These persistent discrepancies suggest that the MSC may introduce substantial bias in estimating treatment effects, raising concerns about the method's validity and the reliability of its conclusions in this context.

In contrast, the HCW method is specifically designed for panel data settings where both cross-sectional and time-series variation are important. It models the treated unit's outcomes as a function of the outcomes of control units and their lagged values, enabling a flexible and data-driven construction of counterfactuals without relying on convexity or subsampling. This approach naturally accommodates multiple time periods, heterogeneous treatment effects, and relatively short pre-treatment periods — all of which are central features of our trade war study.

Unlike the SCM and MSC, which impose non-negativity constraints on control weights, HCW allows for both positive and negative weights. This added flexibility is particularly valuable in complex policy environments like the China–US trade war, where the treated unit may not be well approximated by any convex combination of control units. Furthermore, the HCW framework can be extended to handle nonstationary data, a critical requirement given the macroeconomic nature of our outcome variable.

Overall, the HCW's ability to use the panel structure and capture dynamic relationships across units makes it especially well-suited for estimating treatment effects in this context.

5. Conclusions

This section summarizes the findings from the analysis and offers future research directions and remarks related to this study. Based on the results above, several key conclusions can be drawn. First, the trade war initiated by the US in 2018 has had a substantial impact on China's trade patterns. A more flexible factor model applied in this study reveals that China's exports experienced a significant decline post-2018, as actual export figures fell below the predicted values. This decline is attributable to the US-imposed tariffs on Chinese goods, leading to a noticeable drop in trade volumes. Despite the trade war, China managed to stabilize its exports, possibly by finding alternative markets or adjusting trade strategies. However, the overall negative impact on China's trade surplus is evident, with the predicted trade balance indicating a substantial reduction in China's trade surplus with the US, exceeding $150 millions. The decline in imports was also significant but less pronounced than exports, reflecting China's strategic response to mitigate the impact of US tariffs.

Second, the US trade pattern showed mixed effects due to the trade war with China. While the predicted results indicated a decline in US imports from China, aligning with the initial goal of reducing the trade deficit, US exports to China remained relatively stable and even exceeded predicted predictions post-2020. The overall effect of the trade war on the US trade balance with China was positive in the short term, as it helped reduce the trade deficit. However, the long-term effects might differ and require further analysis.

Third, the trade war has had far-reaching economic effects, with China facing more substantial adverse impacts compared to the US. The significant reduction in China's trade surplus, coupled with the corresponding decrease in the US trade deficit, highlights the direct consequences of the trade conflict. Beyond bilateral trade, the broader economic effects have influenced global trade dynamics, disrupted supply chains, and shaped economic policies, potentially creating indirect and long-lasting repercussions for international trade.

Fourth, the findings of this study provide relevant insights for policymakers dealing with trade disputes. The China–US trade war not only disrupted bilateral trade but also had broader effects on global trade flows and supply chains. The results of this analysis can provide useful insights for future trade negotiations by showing the possible side effects of tariff policies. While tariffs might help reduce trade deficits in the short term, they can also cause shifts in trade patterns and supply chains, leading to long-term economic changes. Policymakers should consider these impacts when making trade decisions to avoid unnecessary disruptions to the economy. The findings also highlight that solving trade conflicts works better when multiple countries are involved, rather than one country acting alone. When a country imposes tariffs on its own, it often leads to more tension and uncertainty, making the situation worse instead of solving the problem. Moving forward, trade policies should consider more stable and cooperative mechanisms to manage disputes and mitigate negative spillover effects.

Finally, the paper by Bai et al. (2014) further supports using the HCW method, particularly when dealing with nonstationary data. Their approach is computationally simpler and avoids the biases present in the traditional SCM, which requires the assumption of no sample selection effects and homogeneous impacts of underlying factors. By applying the HCW method and the dynamic permutation test, our analysis enhances flexibility and robustness in estimating treatment effects, enabling a more precise capture of dynamic changes in trade patterns between China and the US during the trade war. This approach provides valuable insights into the complexities of international trade relationships.

Next, based on the empirical study discussed above, some future research topics should be warranted as follows. First, the results of the US overall trade balance still show an overall deficit, indicating that there may be mediators affecting the results. Future research should explore these mediation effects to provide a deeper understanding of the factors influencing trade dynamics beyond the direct impacts of tariffs and retaliatory measures. Moreover, future studies can combine the traditional SCM with some advanced econometric techniques to improve the accuracy and reliability of the predicted control results. By integrating penalized regression methods and better weight selection approaches, researchers can better capture the underlying trade dynamics and provide more precise estimates of treatment effects. Additionally, some machine learning methods for treatment effect estimation could deliver a better understanding if a high-dimensional covariate is involved.

Furthermore, with Donald Trump now serving a second term as President, his administration has reintroduced aggressive trade measures that highlight the ongoing instability of US trade policy. Citing a national emergency under the International Emergency Economic Powers Act (IEEPA), the administration has imposed a 25% tariff on all imports from Mexico and Canada and a 10% tariff on imports from China, with a lower 10% rate on Canadian energy exports. These tariffs are presented as national security measures, intended to address problems like the flow of fentanyl and other synthetic drugs, as well as illegal immigration. The administration argues that Mexico and Canada have not done enough to stop drug trafficking, and that China plays a role by supplying ingredients used to make fentanyl and supporting the financial networks behind it. On April 2, 2025, Trump announced a 10% "base tariff" on all countries, set to take effect at 12:01 a.m. Eastern Time on April 5. In addition, countries with the largest trade deficits with the US will face higher, customized "reciprocal tariffs" starting at 12:01 a.m. on April 9. Meanwhile, tariffs on Canada and Mexico will be lifted, and all other countries will remain subject to the standard 10% rate. These actions are expected to reshape trade flows in both North America and Asia, adding new layers of geopolitical and policy uncertainty. This supports our main argument that the post-2018 trade environment is marked by structural changes and policy-driven non-stationarity. Future research could explore how such politically driven trade interventions influence the persistence and predictability of trade imbalances, and how forecasting models can adapt to these shifting and uncertain conditions.[10]

[10] We sincerely appreciate the Guest Editor who brought our attention to this issue.

Table 3
Augmented Dickey–Fuller test results for imports data.

Variable	Log levels			Log-first differences		
	None	Drift	Trend	None	Drift	Trend
China	1.0000	1.0000	0.9848	0.9268	0.8347	0.0019***
US	0.9969	0.9456	0.0172	0.0000***	0.0000***	0.0000***
South Korea	0.9996	0.1572	0.2051	0.0871	0.0007***	0.0005***
Japan	0.9983	0.0000***	0.0029***	0.0000***	0.0000***	0.0203
Australia	0.9999	0.2471	0.3538	0.0000***	0.0000***	0.0955
New Zealand	0.9980	0.1027	0.5498	0.0761	0.0018***	0.0004***
Thailand	0.9997	0.1131	0.2137	0.0000***	0.0001***	0.0007***
Vietnam	1.0000	0.3424	1.0000	0.0173	0.0234	0.0215
Malaysia	0.9988	0.9644	0.0000***	0.0000***	0.0114	0.0239
Indonesia	0.9986	0.1715	0.4235	0.0196	0.0890	0.2207
Singapore	0.9999	0.1939	0.0113	0.0000***	0.0017***	0.0853
India	1.0000	0.2262	0.9780	0.0035***	0.0042***	0.0802
Germany	0.9999	0.0849	0.0908	0.0310	0.0526	0.0021***
Italy	0.9995	0.1833	0.7587	0.0620	0.0700	0.1596
France	0.9997	0.4071	0.6841	0.0512	0.1487	0.0004***
South Africa	0.9998	0.3890	0.9700	0.0002***	0.0446	0.0000***
Mexico	0.9972	0.2834	0.6044	0.0001***	0.0001***	0.0007***
Brazil	0.9995	0.8024	0.6565	0.0089***	0.0074***	0.0551
Argentina	0.9927	0.1619	0.0069***	0.0002***	0.0712	0.0382
United Kingdom	0.9994	0.0029***	0.3826	0.0002***	0.0004***	0.0893
Netherlands	0.9999	0.0023***	0.8149	0.0013***	0.0024***	0.0022***
Canada	0.9817	0.1148	0.1841	0.0000***	0.1575	0.0749
Spain	0.9995	0.1286	0.7790	0.0475	0.1253	0.0980
Turkey	0.9999	0.0017***	0.7749	0.0162	0.1035	0.0720
Poland	1.0000	0.0010***	0.5562	0.0467	0.2719	0.2949
Switzerland	1.0000	0.3241	0.5297	0.0548	0.0741	0.6828
United Arab Emirates	1.0000	0.0023***	0.6495	0.0001***	0.0029***	0.0001***
Austria	0.9999	0.1814	0.8874	0.0762	0.1801	0.1557

Note: This table provides detailed p-values of the ADF tests for both log levels and log-first differences on each country imports data under different assumptions. P-values marked with *** indicate significance at the 1% level, implying the rejection of the null hypothesis of non-stationarity.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that they do not use any generative AI and AI-assisted technologies in the writing process.

Declaration of competing interest

The authors claim that there are no relevant financial or non-financial competing interests to report for this article.

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Appendix. Additional adf test results

The appendix provides additional ADF test results, which help illustrate the characteristics of the data. The ADF test results for import data, shown in Table 3, indicate that many countries remain nonstationary even after first differencing. While countries like China, the US, Japan, and South Korea exhibit strong stationarity after first differencing with significant p-values across all test specifications, approximately half of the countries, such as Brazil, Argentina, and Poland, still display non-stationarity under certain conditions. For example, countries like India, Indonesia, and Austria show higher p-values after first differencing, indicating non-stationarity in some cases.

For Table 4, which presents the ADF test results for countries' imports from China, the outcomes show mixed significance across the different specifications. Some countries, such as the US, Japan, and Germany, exhibit significant results after first differencing under certain conditions (e.g., none, drift, or trend), while others, such as South Korea and Australia, show non-significant p-values under specific conditions.

Similarly, Table 5 presents the ADF test results for countries' imports from the US. The results indicate that while many countries' data at log levels show non-significant p-values across all cases, most countries, including Australia, Brazil, France, India, and Italy,

Table 4
ADF Test Results for countries import from China.

Variable	Log Levels			Log-First Differences		
	None	Drift	Trend	None	Drift	Trend
US	0.9656	0.9974	0.2322	0.3522	0.0000***	0.0000***
South Korea	0.9999	0.2941	0.8881	0.0961	0.0002***	0.2330
Japan	0.9999	0.1417	0.8329	0.0476	0.0010***	0.1170
Australia	0.9971	0.0918	0.9844	0.0865	0.0026***	0.3782
New Zealand	1.0000	0.6386	0.9856	0.0908	0.0016***	0.8114
Thailand	0.9999	0.8941	0.5913	0.0284	0.0000***	0.0124
Malaysia	0.9989	0.4979	1.0000	0.1042	0.0009***	0.1418
Indonesia	0.9999	0.4158	0.7571	0.0531	0.0017***	0.6103
Singapore	0.9869	0.5560	0.9357	0.0330	0.0031***	0.2174
India	0.9999	0.4158	0.7571	0.0531	0.0017***	0.6103
Germany	1.0000	0.0000***	0.9805	0.0233	0.0018***	0.3204
Italy	1.0000	0.4624	0.3079	0.1580	0.0001***	0.3811
France	0.8948	0.6926	0.9763	0.1018	0.0041***	0.2275
South Africa	1.0000	0.0000***	0.0000***	0.0796	0.0000***	0.1127
Mexico	0.8087	0.2711	0.9915	0.1580	0.0098***	0.4593
Brazil	0.9999	0.1171	0.9969	0.3494	0.0042***	0.3366
Canada	0.9976	0.1322	0.2970	0.0834	0.0007***	0.4590
Netherlands	1.0000	0.4873	0.9813	0.0805	0.0083***	0.0561
Russia	0.9844	0.9128	0.6458	0.0601	0.0024***	0.4226
United Kingdom	0.9998	0.0008***	0.9648	0.2404	0.0091***	0.1233
Vietnam	0.8341	0.2373	1.0000	0.4866	0.0973	0.6070

Note: This table provides detailed p-values of the ADF tests for both log levels and log-first differences on each country imports from China under different assumptions. P-values marked with *** indicate significance at the 1% level, implying the rejection of the null hypothesis of non-stationarity. At log levels, most of them are nonstationary, while with log-first differences, most of them show a trend but without a drift.

Table 5
ADF test results for countries import from the US.

Variable	Log levels			Log-first differences		
	None	Drift	Trend	None	Drift	Trend
China	0.9994	0.9984	0.1057	0.8182	0.2394	0.1086
Australia	0.9877	0.7068	0.1556	0.0000***	0.0000***	0.0001***
Brazil	0.9998	0.9710	0.2602	0.0004***	0.0133	0.1150
Canada	1.0000	0.3145	0.9946	0.5497	0.0003***	0.0090***
France	0.9926	0.9256	0.2954	0.0003***	0.0006***	0.0055***
Germany	0.9885	0.8607	0.4879	0.0001***	0.0001***	0.0162
India	0.9995	0.8645	0.9170	0.0001***	0.0000***	0.0001***
Israel	0.9778	0.4083	0.4995	0.0000***	0.0000***	0.0065***
Italy	1.0000	0.7918	0.0002***	0.0000***	0.0000***	0.0000***
Japan	0.8601	0.1112	0.8517	0.0000***	0.0000***	0.0532
Korea, Rep.	0.9929	0.5828	0.5647	0.0000***	0.0000***	0.5474
Malaysia	0.9380	0.0010***	0.6613	0.0000***	0.0000***	0.1075
Mexico	0.9992	0.9145	0.7170	0.0000***	0.0086***	0.1023
New Zealand	0.9998	0.9686	0.2349	0.0001***	0.0110	0.0815
Singapore	0.9927	0.1991	0.2886	0.0000***	0.0012***	0.0516
South Africa	0.9051	0.5393	0.4602	0.0000***	0.0000***	0.2624
Switzerland	0.9665	0.7386	0.1491	0.0002***	0.1634	0.4143
Thailand	0.9488	0.4963	0.5741	0.0000***	0.0000***	0.5696
United Kingdom	1.0000	0.9205	0.0000***	0.0002***	0.0002***	0.0061***

Note: This table provides detailed p-values of the ADF tests for both log levels and log-first differences on each country imports from the US. P-values marked with *** indicate significance at the 1% level, implying the rejection of the null hypothesis of non-stationarity. At log levels, most of them are nonstationary, while with log-first differences, most of them are stationary.

demonstrate a clear shift to significance after first differencing. However, countries like Malaysia and New Zealand show mixed results, with non-significant p-values under certain conditions.[11]

[11] To maintain clarity in the paper, the data on countries' exports to China and the US have been omitted to avoid unnecessary complexity, as these results show similar mixed outcomes for stationarity, with some countries remaining nonstationary even after differencing.

Data availability

Data will be made available on request.

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