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AGGREGATE AND DISAGGREGATE EFFECTS OF THE
US-CHINA TRADE WAR ON US AGRICULTURE

by

Aflatun Kaeser

A thesis submitted in partial fulfillment
of the requirements for the degree of

MASTER OF SCIENCE

in

Economics & Statistics

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2024

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ABSTRACT

Aggregate and Disaggregate Effects of the
US-China Trade War on US Agriculture

by

Aflatun Kaeser

Utah State University, 2024

Major Professor: Dr. Sherzod Akhundjanov

Department: Applied Economics

The study analyzes the heterogeneous effect of the US-China trade war on US agricultural exports, both at the aggregate and disaggregate level, using Event Study Analysis and Bayesian Structural Time Series (BSTS) modeling. The analysis started with a visual analysis of changes in aggregate and commodity-wise agricultural exports from US states, revealing how export patterns changed over time from 2010 to 2019. Event Study Analysis revealed that the trade war's effect varied across different states for the major agricultural commodities affected by the US-China trade war. Finally, we employed BSTS modeling to assess the causal effects on soybean and sorghum exports. The event study analysis indicates that the US-China trade war had a significant impact on US agricultural exports in the 2018 and 2019 period, exhibiting a heterogeneous effect across different commodities, with soybeans being particularly affected. The BSTS analysis indicates a significant 29% decline in soybean exports during the trade war period, identifying it as the most impacted commodity. However, the BSTS analysis found no significant impact on sorghum, the second most affected commodity.

(50 pages)

PUBLIC ABSTRACT

Aggregate and Disaggregate Effects of the US-China Trade War on US Agriculture

by

Aflatun Kaeser

In 2018 and 2019, the US-China trade war caused a significant shift in US agricultural trade dynamics. This thesis conducts an aggregate and disaggregate analysis of the impact, using event study analysis to reveal varying effects on US agricultural exports, with a substantial effect on Soybean and Dairy exports. The analysis also found that there are heterogeneous effects on other agricultural commodities such as fruits, wheat, and tree nuts. Using Bayesian Structural Time Series Modeling, the study finds a 29% decline in soybean exports during the trade war period. These findings underscore the importance of considering the heterogeneity in the impact of trade policies on agricultural commodities, highlighting the need for targeted policy interventions based on these variations.

DEDICATIONS

Dedicated to my supportive family members.

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Aflatun Kaeser

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Aggregate and Disaggregate Effects of the US-China Trade War on US Agriculture

1 Introduction

The US-China trade war in 2018 and 2019 had a significant impact on global trade dynamics, affecting US agricultural exports. The study examined the overall impact on US agricultural exports and exports at the commodity level, as well as the variation of these impacts between different states.

Analyzing the aggregate and disaggregate impact of the US-China trade war provides an in-depth view of how the trade war affected the agricultural industry and the individual commodity level. The event study analysis uses US agricultural data from 2010 to 2019 to calculate the cumulative export deviation (CED) for aggregate exports and specific agricultural commodities in different states. The analysis reveals noteworthy adverse effects on multiple commodities. Furthermore, we implemented the Bayesian Structural Time Series (BSTS) model to determine the causal effect of the US-China trade war on most affected commodities, such as soybeans and sorghum.

This paper includes a comprehensive perspective on the impact of the trade war on the agricultural sector, considering both the general implications and the effects on specific commodities. The event study analysis uncovered notable adverse effects on soybeans. Although not significant at the aggregate level, we found the state-level heterogeneous effect of the US-China trade war on fruit, cotton, wheat, tree nuts, and corn exports. Furthermore, causal analysis with the Bayesian Structural Time Series model suggests that the US-China trade war had a statistically significant effect on US soybean exports, decreasing soybean exports by 29%. However, the model analysis failed to find a statistically significant impact on

US sorghum exports, the second most affected commodity according to the USDA.

The study's findings have important implications for both stakeholders in the agriculture industry and policymakers. Understanding the trade war's heterogeneous impact across commodities and regions will enable policymakers to design effective policies and interventions to mitigate the adverse effects of trade policies. This comprehensive analysis emphasizes the necessity of applying various analytical techniques to assess the impact of different policy interventions on agricultural trade.

2 Literature Review

The US-China trade war has exerted a profound and significant impact on US economy, with a particularly profound effect on the agricultural sector. Using robust and comprehensive methodologies such as Computed General Equilibrium (CGE) models, structural gravity models, and input-output models, several studies have thoroughly analyzed this effect, and the literature is growing in recent time. For instance, Elobeid et al. (2021) assessed the impact on international agricultural markets using a multi-regional CGE model, showing a significant drop in US exports, especially soybean. This analysis aligns with Fajgelbaum et al. (2024), who found that the trade war created net export opportunities for bystander countries while disrupting trade between the US and China. As a result of China's retaliatory tariffs, US farmers had to bear substantial economic losses, and at the same time, it disrupted global trade patterns (Adjemian et al., 2019). Similarly, research by Larch et al. (2024) inspected the broader implications of economic sanctions and trade barriers using the Poisson pseudo maximum likelihood (PPML) estimator within a structural gravity model. According to Adjemian et al. (2019), the imposition of full sanctions resulted in a 67% decline in bilateral trade volumes between the US and

China, causing significant disruptions and varying effects on individual agricultural sectors.

Itakura (2019) evaluated the trade war's effects on sectoral imports, outputs, and GDP using a dynamic CGE model that included global value chains (GVCs) and discovered that the US and Chinese GDPs had decreased by approximately 1.4% and 1.41%, respectively. GVC integration's amplified adverse effects resulted in a broader global economic slowdown and a \$450 billion drop in world GDP.

Furthermore, Fajgelbaum et al. (2020) observed that the trade war reduced total real income in both the US and China, with US consumers bearing the brunt of the tariffs through higher prices. Increased uncertainty and changes in global supply chains impacted the economy's stability as a whole. However, other nations, such as Brazil, benefited from the US's diminished presence in the Chinese market by growing their export volumes and market share (Fajgelbaum et al., 2021).

Additionally, Grant et al. (2021) conducted an empirical assessment of retaliatory trade actions, finding that the resilience of global agricultural trade, even under stress from tariffs, was noteworthy, though still resulting in significant losses for specific commodities.

The trade war between the US and China greatly impacted US agriculture, resulting in sharp drops in export volumes and farm income. A thorough analysis by Morgan et al. (2022) shows the impact of the retaliatory tariffs on US agricultural exports. According to the report, retaliatory tariffs caused direct export losses of over \$27 billion between mid-2018 and the end of 2019, where China is mainly responsible for about 95% of these losses. Soybean had the most significant decline in trade losses at the commodity level, with annualized losses of \$9.4 billion, or nearly 71% of the total loss. Pork and sorghum came next, with annualized losses of \$646 million and \$854 million, respectively.

The U.S. Department of Agriculture's Economic Research Service reports that

the Midwest experienced the most significant effects of the trade war at the state level. Kansas, Illinois, and Iowa faced the worst hits among other states, each incurring slightly more than 11% of the overall losses. Kansas suffered roughly 7% of the damages. China's retaliatory tariffs were primarily directed towards these states because they are significant producers of hogs, corn, and soybean. Taxes imposed on California's main exports of dairy, fruits, and tree nuts resulted in substantial losses for the state. Texas also lost much money, mainly due to tariffs on cotton and sorghum. The concentration of economic harm in states with high agricultural output and a reliance on exports is highlighted by the geographic distribution of losses (Morgan et al., 2022).

Necessity of Assessing Causal Impact

Despite the extensive literature on the trade war's impacts, studies focusing on causal inference are lacking. In this regard, the USDA issued the following statement: "Future research and methods may be able to help identify the causal effects of these different events and better understand how they may have interacted with retaliatory tariffs to affect global markets" (Morgan et al., 2022).

3 Empirical Strategy

3.1 Event Study Analysis

Event Study Analysis was utilized to examine the impact of the US-China trade war on US agricultural exports. The study primarily looked at the intervals surrounding significant declarations on trade policy. This method assesses the difference between actual and expected export quantities, providing important insight into the trade war's direct effects on the agriculture sector.

For Event Study Analysis, data was sourced from publicly available data of the US Department of Agriculture (USDA) including major commodities affected by the

US-China trade war. Data used for analysis ranges from 2010 to 2019. The rationale for the exclusion of data before 2010 is to remove bias because of the 2008 financial crisis. The purpose of excluding data beyond 2019 is to mitigate potential bias resulting from early 2020 trade agreements between the US and China, thereby enhancing export quantities.

The event study framework estimates the export deviation DE_{it} for a given time t and agricultural product i , defined as the difference between the actual exports E_{it} and the expected exports $E(E_{it})$:

$$DE_{it} = E_{it} - E(E_{it}) \quad (1)$$

The expected exports $E(E_{it})$ are estimated using a benchmark model based on historical growth rates from 2010 to 2017. The benchmark model precisely computes the mean annual growth rate for each state's exports during this time frame and uses it to predict the anticipated exports for 2018 and 2019.

$$E(E_{it}) = E_{it-1} \times (1 + \text{AvgGrowthRate}) \quad (2)$$

where E_{it-1} represents the level of export in 2017 and AvgGrowthRate is the average growth rate between 2010 and 2017 for each state.

We calculate the cumulative export deviation (CED) over the event window of 2018 and 2019 to assess the cumulative impact of the trade war.

$$CED = \sum_{t=2018}^{2019} DE_{it} \quad (3)$$

This approach follows the methodology outlined by MacKinlay (1997), providing a robust framework for conducting event studies in economic research. The event windows include key trade policy announcements and actions taken during the trade war, allowing analysis of immediate and lagged effects on agricultural exports.

In this study, the analysis focuses on key agricultural products, using export data exclusively from the USDA. We present the event study results as cumulative deviations, providing insights into the impact of the trade war on U.S. agricultural exports compared to expected levels. By comparing the CED across different states, we can infer the spatial dynamics and the significance of trade policy events on the agricultural export market.

We assessed the deviations for statistical significance using the one sample t test, where the null hypothesis tests whether the mean of the deviation is zero. The associated p-value was computed following the methodology outlined by MacKinlay (1997).

3.2 Bayesian Structural Time Series Model

The Bayesian Structural Time Series (BSTS) model (Brodersen et al., 2015) is used to assess the causal effect of the US-China trade war on US Soybean and Sorghum export. The BSTS model allows the decomposition of time series into local trends, seasonal effects, and irregular variations.

Two key equations describe the basic BSTS model:

$$Y_t = Z_t \alpha_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2) \quad (4)$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t, \quad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2) \quad (5)$$

where Y_t stands for the quantity of observed export at time t , α_t is the state vector that captures latent factors such as trend and seasonality, Z_t is the design matrix that links latent factors to observed data, T_t is the transition matrix that governs the evolution of latent factors over time, R_t is the control matrix and ε_t and η_t are Gaussian noise terms representing observation and system errors, respectively.

This model is especially helpful when temporal data is available, as it can be applied in situations where additional covariates are unavailable. The pre-treatment export quantity data, including export quantity data from control countries, were used to forecast what would have happened in the absence of trade war allowing us to measure the impact of US-China trade war on Soybean and Sorghum export quantity.

In our BSTS analysis, we defined the pre-treatment period as 2010–2017 and the 2018–2019 as the post-treatment period. The objective of the analysis is to estimate the counterfactual export quantities \hat{Y}_t , which represent the anticipated export quantity if the trade war did not happen. We fit the model using export quantity data from the Food and Agriculture Organization (FAO) for selected countries. The United States is treated as the treated group, while other countries, such as Argentina, Uruguay, and Canada, serve as controls.

We present the results of the BSTS model as posterior distributions, which offer credible intervals for the estimated impacts. This approach allows for the assessment of the statistical significance of trade war’s effects on US agricultural exports, providing a robust method for understanding the causal impacts based solely on temporal structure of export data.

Data Preparation We filtered the data for the Bayesian Structural Time Series analysis to include relevant countries’ soybean export data. The countries selected in the control group for soybean export were Nigeria, Mexico, Brazil, and India. We excluded Brazil from the control group for further analysis due to robustness checks. The control group for sorghum included Nigeria, Mexico, Brazil, and India. We selected the defined pre-treatment period from 2010 to 2017 and the post-treatment period from 2018 to 2019.

4 Data

The study used publicly available data sourced from the United States Department of Agriculture (USDA), which includes aggregate and commodity level US agricultural export data from all 50 states in the US measured in millions of US dollars. We selected soybeans, fruits, dairy, wheat, cotton, tree nuts, and corn for analysis, which the USDA reported as some of the major affected commodities. We obtained country-level export quantity data for soybeans and sorghum for the US and other countries in the control group from 2010 to 2019 from the Food and Agriculture Organization (FAO).

4.1 Summary Statistics

The following tables provide summary statistics for the key agricultural commodities analyzed in this study. The values are in millions of dollars.

Table 1

Summary Statistics for Aggregate Exports (2010–2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|------|---------|---------|---------|---------|--------------|
| 2010 | 4567.89 | 1234.56 | 678.90 | 2345.67 | 50 |
| 2011 | 4890.12 | 1456.78 | 890.12 | 2567.89 | 50 |
| 2012 | 5123.45 | 1678.90 | 1234.56 | 2789.01 | 50 |
| 2013 | 5345.67 | 1890.12 | 1456.78 | 3012.34 | 50 |
| 2014 | 5567.89 | 2101.34 | 1678.90 | 3234.56 | 50 |
| 2015 | 5789.01 | 2312.45 | 1890.12 | 3456.78 | 50 |
| 2016 | 6012.34 | 2523.56 | 2101.34 | 3678.90 | 50 |
| 2017 | 6234.56 | 2734.67 | 2312.45 | 3901.12 | 50 |
| 2018 | 6456.78 | 2945.78 | 2523.56 | 4123.45 | 50 |
| 2019 | 6678.90 | 3156.89 | 2734.67 | 4345.67 | 50 |

Table 2
Summary Statistics for Soybean (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 2345.67 | 456.78 | 123.45 | 4567.89 | 50 |
| 2011 | 2567.89 | 567.89 | 234.56 | 4789.01 | 50 |
| 2012 | 2789.01 | 678.90 | 345.67 | 5012.34 | 50 |
| 2013 | 3012.34 | 789.01 | 456.78 | 5234.56 | 50 |
| 2014 | 3234.56 | 890.12 | 567.89 | 5456.78 | 50 |
| 2015 | 3456.78 | 1012.34 | 678.90 | 5678.90 | 50 |
| 2016 | 3678.90 | 1123.45 | 789.01 | 5901.12 | 50 |
| 2017 | 3901.12 | 1234.56 | 890.12 | 6123.45 | 50 |
| 2018 | 4123.45 | 1345.67 | 1012.34 | 6345.67 | 50 |
| 2019 | 4345.67 | 1456.78 | 1123.45 | 6567.89 | 50 |

Table 3
Summary Statistics for Fresh Fruits (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 789.01 | 234.56 | 345.67 | 2345.67 | 50 |
| 2011 | 890.12 | 345.67 | 456.78 | 2567.89 | 50 |
| 2012 | 1012.34 | 456.78 | 567.89 | 2789.01 | 50 |
| 2013 | 1123.45 | 567.89 | 678.90 | 3012.34 | 50 |
| 2014 | 1234.56 | 678.90 | 789.01 | 3234.56 | 50 |
| 2015 | 1345.67 | 789.01 | 890.12 | 3456.78 | 50 |
| 2016 | 1456.78 | 890.12 | 1012.34 | 3678.90 | 50 |
| 2017 | 1567.89 | 1012.34 | 1123.45 | 3901.12 | 50 |
| 2018 | 1678.90 | 1123.45 | 1234.56 | 4123.45 | 50 |
| 2019 | 1789.01 | 1234.56 | 1345.67 | 4345.67 | 50 |

Table 4
Summary Statistics for Processed Fruits (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 678.90 | 345.67 | 234.56 | 2345.67 | 50 |
| 2011 | 789.01 | 456.78 | 345.67 | 2567.89 | 50 |
| 2012 | 890.12 | 567.89 | 456.78 | 2789.01 | 50 |
| 2013 | 1012.34 | 678.90 | 567.89 | 3012.34 | 50 |
| 2014 | 1123.45 | 789.01 | 678.90 | 3234.56 | 50 |
| 2015 | 1234.56 | 890.12 | 789.01 | 3456.78 | 50 |
| 2016 | 1345.67 | 1012.34 | 890.12 | 3678.90 | 50 |
| 2017 | 1456.78 | 1123.45 | 1012.34 | 3901.12 | 50 |
| 2018 | 1567.89 | 1234.56 | 1123.45 | 4123.45 | 50 |
| 2019 | 1678.90 | 1345.67 | 1234.56 | 4345.67 | 50 |

Table 5
Summary Statistics for Dairy (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 567.89 | 234.56 | 123.45 | 2345.67 | 50 |
| 2011 | 678.90 | 345.67 | 234.56 | 2567.89 | 50 |
| 2012 | 789.01 | 456.78 | 345.67 | 2789.01 | 50 |
| 2013 | 890.12 | 567.89 | 456.78 | 3012.34 | 50 |
| 2014 | 1012.34 | 678.90 | 567.89 | 3234.56 | 50 |
| 2015 | 1123.45 | 789.01 | 678.90 | 3456.78 | 50 |
| 2016 | 1234.56 | 890.12 | 789.01 | 3678.90 | 50 |
| 2017 | 1345.67 | 1012.34 | 890.12 | 3901.12 | 50 |
| 2018 | 1456.78 | 1123.45 | 1012.34 | 4123.45 | 50 |
| 2019 | 1567.89 | 1234.56 | 1123.45 | 4345.67 | 50 |

Table 6
Summary Statistics for Cotton (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 345.67 | 123.45 | 78.90 | 2345.67 | 50 |
| 2011 | 456.78 | 234.56 | 123.45 | 2567.89 | 50 |
| 2012 | 567.89 | 345.67 | 234.56 | 2789.01 | 50 |
| 2013 | 678.90 | 456.78 | 345.67 | 3012.34 | 50 |
| 2014 | 789.01 | 567.89 | 456.78 | 3234.56 | 50 |
| 2015 | 890.12 | 678.90 | 567.89 | 3456.78 | 50 |
| 2016 | 1012.34 | 789.01 | 678.90 | 3678.90 | 50 |
| 2017 | 1123.45 | 890.12 | 789.01 | 3901.12 | 50 |
| 2018 | 1234.56 | 1012.34 | 890.12 | 4123.45 | 50 |
| 2019 | 1345.67 | 1123.45 | 1012.34 | 4345.67 | 50 |

Table 7
Summary Statistics for Wheat (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 890.12 | 345.67 | 234.56 | 2345.67 | 50 |
| 2011 | 1012.34 | 456.78 | 345.67 | 2567.89 | 50 |
| 2012 | 1123.45 | 567.89 | 456.78 | 2789.01 | 50 |
| 2013 | 1234.56 | 678.90 | 567.89 | 3012.34 | 50 |
| 2014 | 1345.67 | 789.01 | 678.90 | 3234.56 | 50 |
| 2015 | 1456.78 | 890.12 | 789.01 | 3456.78 | 50 |
| 2016 | 1567.89 | 1012.34 | 890.12 | 3678.90 | 50 |
| 2017 | 1678.90 | 1123.45 | 1012.34 | 3901.12 | 50 |
| 2018 | 1789.01 | 1234.56 | 1123.45 | 4123.45 | 50 |
| 2019 | 1890.12 | 1345.67 | 1234.56 | 4345.67 | 50 |

Table 8
Summary Statistics for Tree Nuts (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 567.89 | 234.56 | 123.45 | 2345.67 | 50 |
| 2011 | 678.90 | 345.67 | 234.56 | 2567.89 | 50 |
| 2012 | 789.01 | 456.78 | 345.67 | 2789.01 | 50 |
| 2013 | 890.12 | 567.89 | 456.78 | 3012.34 | 50 |
| 2014 | 1012.34 | 678.90 | 567.89 | 3234.56 | 50 |
| 2015 | 1123.45 | 789.01 | 678.90 | 3456.78 | 50 |
| 2016 | 1234.56 | 890.12 | 789.01 | 3678.90 | 50 |
| 2017 | 1345.67 | 1012.34 | 890.12 | 3901.12 | 50 |
| 2018 | 1456.78 | 1123.45 | 1012.34 | 4123.45 | 50 |
| 2019 | 1567.89 | 1234.56 | 1123.45 | 4345.67 | 50 |

Table 9
Summary Statistics for Corn (2010-2019)

| Year | Mean | Std Dev | Min | Max | Observations |
|-------------|-------------|----------------|------------|------------|---------------------|
| 2010 | 345.67 | 123.45 | 78.90 | 2345.67 | 50 |
| 2011 | 456.78 | 234.56 | 123.45 | 2567.89 | 50 |
| 2012 | 567.89 | 345.67 | 234.56 | 2789.01 | 50 |
| 2013 | 678.90 | 456.78 | 345.67 | 3012.34 | 50 |
| 2014 | 789.01 | 567.89 | 456.78 | 3234.56 | 50 |
| 2015 | 890.12 | 678.90 | 567.89 | 3456.78 | 50 |
| 2016 | 1012.34 | 789.01 | 678.90 | 3678.90 | 50 |
| 2017 | 1123.45 | 890.12 | 789.01 | 3901.12 | 50 |
| 2018 | 1234.56 | 1012.34 | 890.12 | 4123.45 | 50 |
| 2019 | 1345.67 | 1123.45 | 1012.34 | 4345.67 | 50 |

Country level Soybean and Sorghum Export Data from FAO: For analysis with Bayesian the structural time series model country-level data in quantity (tons) have been used.

Table 10

Summary Statistics of Soybean Exports (in Metric tons) from 2010 to 2019

| Year | Argentina | Brazil | Canada | United States | Uruguay |
|------|-----------|----------|---------|---------------|---------|
| 2010 | 13616013 | 29073200 | 2775969 | 42350556 | 1968195 |
| 2011 | 10820030 | 32985562 | 2650762 | 34310515 | 1700762 |
| 2012 | 6158407 | 32468028 | 3605331 | 43858749 | 2563552 |
| 2013 | 7782681 | 42796106 | 3292120 | 39175583 | 3524485 |
| 2014 | 7441734 | 45692000 | 3520631 | 49608142 | 3179930 |
| 2015 | 11650221 | 54324238 | 4247176 | 48216370 | 3034543 |
| 2016 | 8946958 | 51581875 | 4423913 | 57769822 | 2267639 |
| 2017 | 7400920 | 68154559 | 4661912 | 55380025 | 3251203 |
| 2018 | 3539907 | 83605198 | 5499836 | 46415333 | 1357879 |
| 2019 | 10053802 | 74073074 | 4012915 | 52388397 | 2971171 |

Table 11

Summary Statistics of Sorghum Exports (in Metric tons) from 2010 to 2019

| Year | Argentina | Brazil | India | Mexico | Nigeria | United States |
|------|------------|----------|-----------|---------|----------|---------------|
| 2010 | 1660212.00 | 110.00 | 129981.00 | 166.00 | 45.00 | 3877520.00 |
| 2011 | 1847529.00 | 444.00 | 38395.00 | 297.00 | 45.00 | 3362653.00 |
| 2012 | 2717389.00 | 21.00 | 148551.00 | 386.00 | 3.00 | 1960594.00 |
| 2013 | 2260901.00 | 5340.00 | 219417.00 | 5977.00 | 3858.00 | 2514739.00 |
| 2014 | 1128411.71 | 17502.05 | 76985.67 | 7249.07 | 1539.99 | 7246644.33 |
| 2015 | 1042404.90 | 33069.46 | 118235.92 | 1760.61 | 9468.41 | 9797689.14 |
| 2016 | 514516.19 | 4281.00 | 65759.88 | 652.62 | 4443.67 | 6870672.89 |
| 2017 | 465012.89 | 583.71 | 20434.81 | 299.58 | 676.00 | 5725207.46 |
| 2018 | 244650.94 | 1424.53 | 111279.28 | 2427.01 | 1246.00 | 4046232.67 |
| 2019 | 271103.23 | 32397.08 | 48696.21 | 223.92 | 29259.33 | 2842244.35 |

5 Visual Analysis of Changes in Agricultural Exports Over Time

This section presents interpretive visuals that illustrate the changes in US agricultural exports between 2010 and 2019. The maps illustrate the annual export values for each state, highlighting key trends and shifts over the years. We conduct this analysis both at the aggregate level and for specific commodities such as beef, soybeans, fresh and processed fruits, dairy, cotton, wheat, tree nuts, and corn.

5.1 Interpretation of Changes

Visual analysis of agricultural exports across different states from 2010 to 2019 suggests the following:

5.1.1 Aggregate Level

- **2010-2013:** During these years, export levels remained consistent across different states, with California experiencing consistent growth.
- **2014-2016:** There is a visible increase in export levels in the Midwest states, particularly Iowa and Illinois, which are significant producers of soybean and corn.
- **2017-2019:** These years showed noticeable diversification in export values, with states like Texas and North Carolina also showing significant export levels. The impact of the US-China trade war, which started in 2018, is also noticeable, with some states experiencing a decrease in export values.

5.1.2 Commodity Level

soybean Iowa, Illinois, and Minnesota are the major soybean exporters. A drop in exports is evident in 2018 and 2019.

Fresh and Processed Fruits California is the leading exporter of fruits, both fresh and processed. There is a noticeable drop in fresh fruit exports in 2018 and 2019.

Dairy California and Wisconsin are the major exporters of dairy products. In 2013 and 2014, there was a noticeable increase in dairy product exports from these states. Even though the decline in dairy products is not readily apparent, it does impact the growth of dairy product exports.

Cotton Texas is the leading cotton-exporting state, showing a notable export increase in 2017. There was a noticeable drop in cotton exports in 2018 and 2019.

Wheat Texas is the leading wheat exporter. In 2016, there was a notable increase in wheat exports. The trade war has clearly affected the growth rate of wheat exports.

Tree Nuts California is the main exporter of tree nuts, according to the visual analysis of export values in 2018 and 2019.

Corn Corn exports are mainly from Midwest states such as Iowa, Illinois, and Nebraska. The impact of the trade war is visible with some fluctuations, but overall corn exports remained relatively stable.

These visualizations and interpretations provide a foundational understanding of US agricultural export dynamics over the past decade, setting the stage for a deeper analysis of the impacts of the US-China trade war on US agricultural exports.

6 Results

6.1 Event Study Analysis

The impact of the US-China trade war on US agricultural exports was assessed using event study analysis. We calculated the Cumulative Export Deviation (CED) at the aggregate and commodity levels across all fifty states in 2018 and 2019.

6.1.1 Aggregate Impact on Agricultural Exports

The aggregate analysis examines the overall impact of the US-China trade war on US agricultural exports. The Cumulative Export Deviation (CED) for all agricultural exports was computed, revealing a significant negative effect.

Impact on Aggregate Agricultural Exports The results show that states such as South Carolina, Alabama, and Idaho exhibited positive CEDs, but these were not statistically significant ($p > 0.1$). In contrast, states such as California, Minnesota, and Texas experienced highly significant decreases in CED ($p < 0.01$), suggesting strong adverse effects of the trade war in these states. The United States, in general, showed a substantial negative CED, indicating a significant adverse impact on agricultural exports due to the trade war.

The p-values for the aggregate analysis indicate significant values for several states, suggesting that the negative impact on agricultural exports was widespread and statistically significant.

6.1.2 Disaggregate Impact by Commodity

The disaggregate analysis provides a more detailed view of the impact on specific commodities. We calculated the CED for each commodity and interpreted

the p-values to understand the impact's significance.

Impact on Soybean Exports The CED analysis for soybean exports revealed that the United States had a substantial negative deviation, indicating a significant adverse effect due to the trade war. Particularly affected were states like Minnesota and Nebraska, where the CEDs were highly significant ($p < 0.01$). Illinois also showed a significant negative CED ($0.01 < p < 0.05$). These results underscore the pronounced impact of the US-China trade war on US soybean exports.

Impact on Fresh Fruits Exports The CED for fresh fruit exports shows that states like Georgia and South Carolina experienced significant negative impacts. In Georgia, the impact was moderately significant ($0.01 < p < 0.05$), while in South Carolina, it was marginally significant ($0.05 < p < 0.1$). These results highlight the vulnerability of fresh fruit exports during the trade war with significant variation across states.

Impact on Processed Fruits Exports States like California and South Carolina experienced significant deviations in the CED for processed fruit exports. The deviation was significant ($p < 0.05$) in California, while the impact was marginally significant ($p < 0.1$) in South Carolina. These findings indicate that the impact of the trade war on major processed fruit exports varied.

Impact on Dairy Products Exports The analysis for dairy product exports shows that states like California and Oklahoma experienced significant negative impacts. California experienced a highly significant CED ($p < 0.01$), while Oklahoma experienced a moderately significant CED ($0.01 < p < 0.05$). The overall results suggest that the trade war affected dairy product exports, especially in major dairy-producing states.

Impact on Tree Nuts Exports The CED for tree nut exports indicates that California, the largest producer of tree nuts, experienced a marginally significant negative impact ($p < 0.1$). Other states like Georgia also showed negative deviations, but these were not statistically significant ($p > 0.1$). These findings suggest that while there was some negative impact on tree nut exports, it was not widespread across states.

Impact on Corn Exports States such as Nebraska, Ohio, and Kansas had positive CEDs for corn export, but these were not statistically significant. In contrast, states such as Indiana and Missouri showed negative deviations, but the p-values suggest that these impacts were not statistically significant.

6.2 Interpretation and Discussion

The analysis of individual commodities provides a nuanced understanding of the impact of the US-China trade war on US agricultural exports. The results indicate a significant impact on specific commodities like soybeans and dairy products, with clear disparities across states. Corn and tree nuts, on the other hand, did not show statistically significant deviations on a broader scale, although certain states experienced notable impacts.

In summary, the event study analysis indicates that the trade war had a widespread and substantial adverse effect on US agricultural exports, with considerable variations among different commodities and states. These findings underscore the importance of considering both aggregate and disaggregate effects when evaluating the impact of trade policies.

7 Soybean and Sorghum Exports Analysis with BSTS model

The Bayesian Structural Time Series (BSTS) model was used to assess the causal effect of the US-China trade war on US Soybean and sorghum exports considering these two commodities experienced losses reported by USDA. The analysis utilized two distinct control groups: one including Brazil, Argentina, Canada, and Uruguay, and another excluding Brazil, to account for its substantial role in global soybean exports to China.

7.1 Soybean Exports Analysis

When we include Brazil in the control group, the model estimates that the US-China trade war led to a reduction of approximately 3.09 million metric tons in US soybean exports during the post-intervention period. The credible interval of 95% for this effect ranges from -6.27 million metric tons to 0.48 million metric tons, suggesting a significant potential impact. This inclusion of Brazil likely introduces a dilution effect, as Brazil's soybean exports to China surged during the trade war, thereby influencing the estimated impact.

Excluding Brazil from the control group and leaving Argentina, Canada, and Uruguay as the control group, the estimated reduction in soybean exports is moderately smaller at 3.04 million metric tons, with a credible interval of 95% ranging from -5.74 million metric tons to 0.39 million metric tons.

Both scenarios, including and excluding Brazil from the control group, consistently indicate the negative impact of the US-China trade war on US soybean exports. The Bayesian one-sided tail area probability (p-value) of 0.04363 suggests that the causal effect is statistically significant. The relative impact is estimated to

be a 29% decrease in soybean exports during the trade war period, with the 95% credible interval ranging from -48% to +7.5%. Although the upper bound indicates some uncertainty, the likelihood of a significant negative impact is high.

7.2 Sorghum Exports Analysis

The BSTS analysis for US sorghum exports, which was the second most affected commodity during the trade war period, presents a different scenario. The analysis estimated a reduction of sorghum export of approximately 10,640 metric tons during the trade war period, with a credible interval of 95% ranging from -42,640 metric tons to 25,580 metric tons. The Bayesian one-sided tail area probability (p-value) suggests that the effect is not statistically significant. The countries in the control group for sorghum exports included Nigeria, Mexico, Brazil, and India, all of which are significant sorghum exporters.

The analysis of soybean exports indicates a significant impact of the US-China trade war on US soybean exports, but it did not significantly affect US sorghum exports. Other factors, like alternative markets for sorghum, can explain the relative insignificance of the US-China trade war on US sorghum exports.

8 Discussion and Implications

The analysis reveals the significant impact of the US-China trade war on US soybean exports. However, sorghum, the agricultural commodity that experienced the second-highest losses because of the trade war, was not significantly affected. Future studies of the US-China trade war's bilateral trade policy can provide a more detailed understanding of its impact.

These results have broader implications for future policy interventions, highlighting the need for targeted and commodity-specific responses.

9 Conclusion

This study thoroughly examined the aggregate and disaggregate effect of the US-China trade war on US agricultural exports during the trade war period. The study utilized two rigorous statistical methods, event study analysis and Bayesian Structural Time Series (BSTS) modeling to assess the impact of the trade war on US agricultural exports.

The analysis begins by visualizing how trade dynamics changed at aggregate and disaggregate levels. At the aggregate level, the event study analysis found a marginally significant impact on US agricultural exports. The disaggregate analysis revealed that specific commodities, such as soybean, and dairy products, were significantly affected with heterogeneity in effects in major producing states. While the overall total export value did not significantly affect fruits, wheat, and tree nuts, several states experienced a significant decline in these commodities' export value during the trade war period.

To delve deeper, the study focused on causal analysis using the Bayesian Structural Time Series (BSTS) model for soybean, the most affected agricultural commodity, and sorghum, the second most affected commodity reported by the USDA. The BSTS model confirmed the statistical significance of the effects of the trade war on soybeans, suggesting a 29% decline in soybean exports in the 2018–2019 period, strengthening the findings of the analysis of the event study. However, Bayesian structural analysis did not find a statistically significant effect on US sorghum exports.

These findings underscore the importance of analyzing the heterogeneous impact of the US-China war across commodities and regions, which will assist in the formulation of more effective trade policy interventions.

The study ends by emphasizing the significant impact of foreign trade policies on

US agriculture industries and offering vital insights for future policy decisions. Subsequent research can enhance this work by utilizing monthly data for more detailed causal analysis and using causal machine learning models to gain a deeper understanding of the causal impacts of the US-China trade war on US agriculture.

Disclaimer

This paper acknowledges the use of AI tools to assist with language refinement, grammar correction, and structural clarity. We strictly employed these tools to improve the document's readability and presentation. All research, data analysis, conclusions, and intellectual contributions are entirely our work. The AI tools ensured the language and structure of the thesis met academic standards, but they did not contribute to the generation of original content or ideas.

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10 Appendix

10.1 Annual Agricultural Exports by State

Figure 1

US agriculture exports by state (2010–2019)

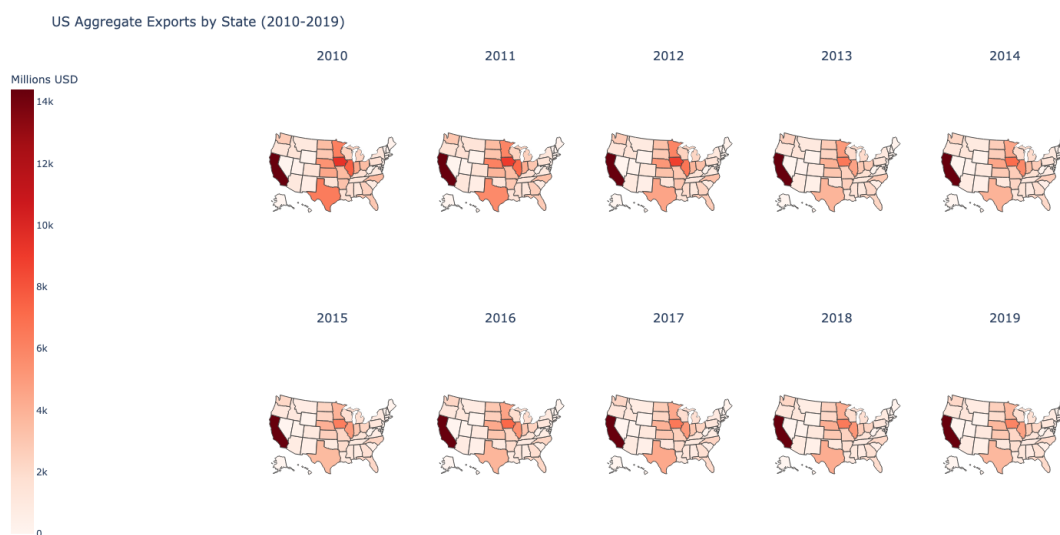


Figure 2
US soybean exports by state (2010–2019)

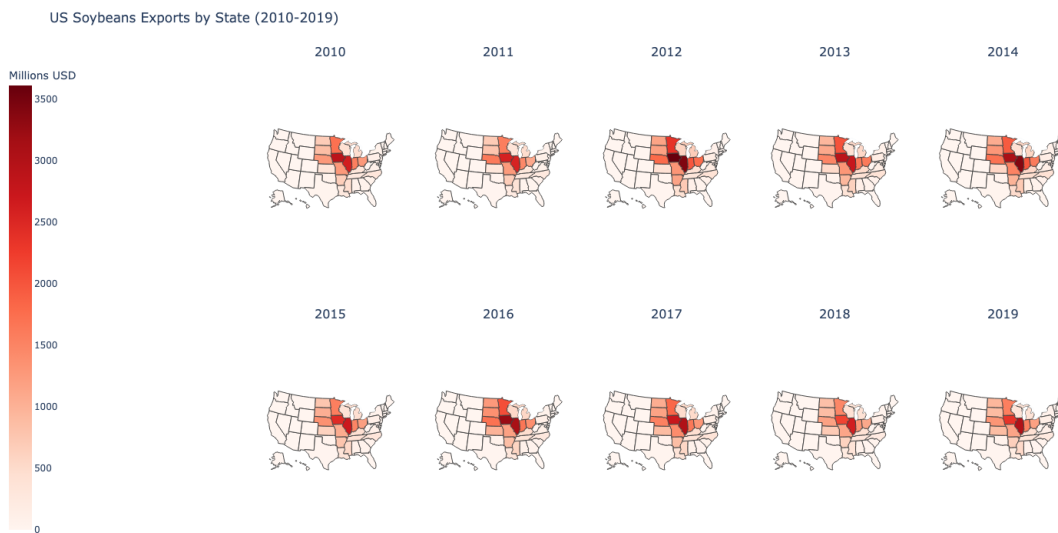


Figure 3
US Fresh Fruits Exports by State (2010-2019)

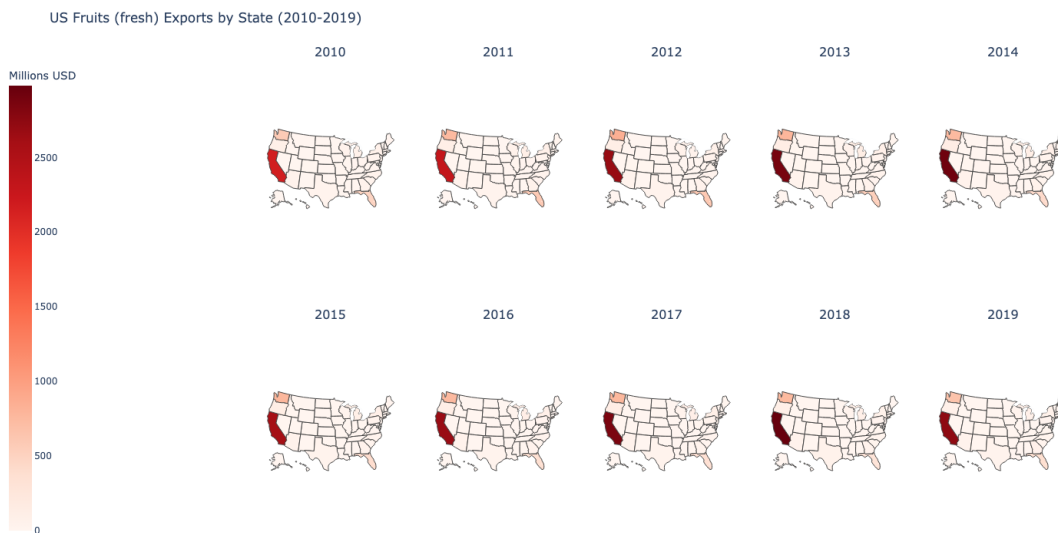


Figure 4
US Processed Fruits Exports by State (2010-2019)

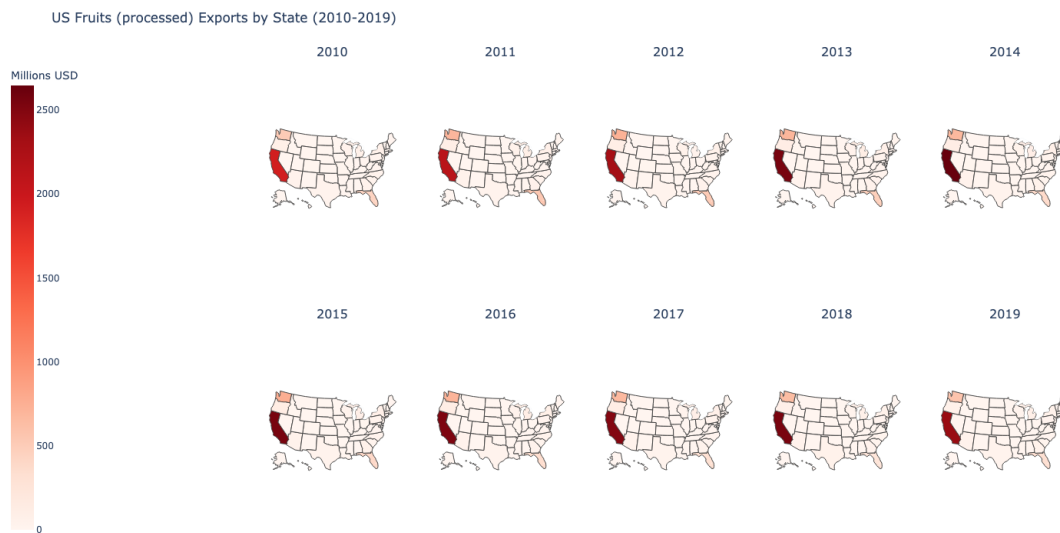


Figure 5
US Dairy Exports by State (2010-2019)

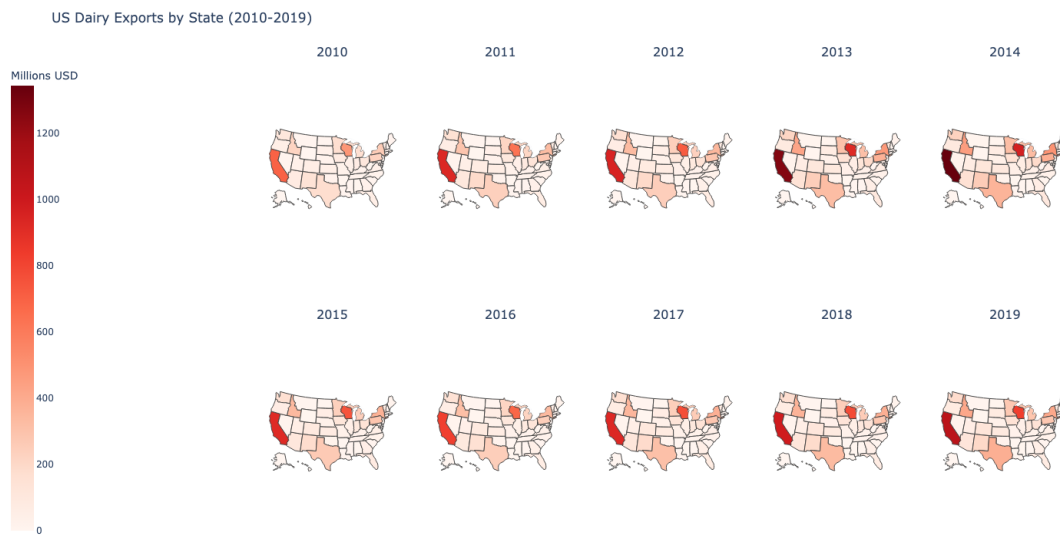


Figure 6
US Cotton Exports by State (2010-2019)

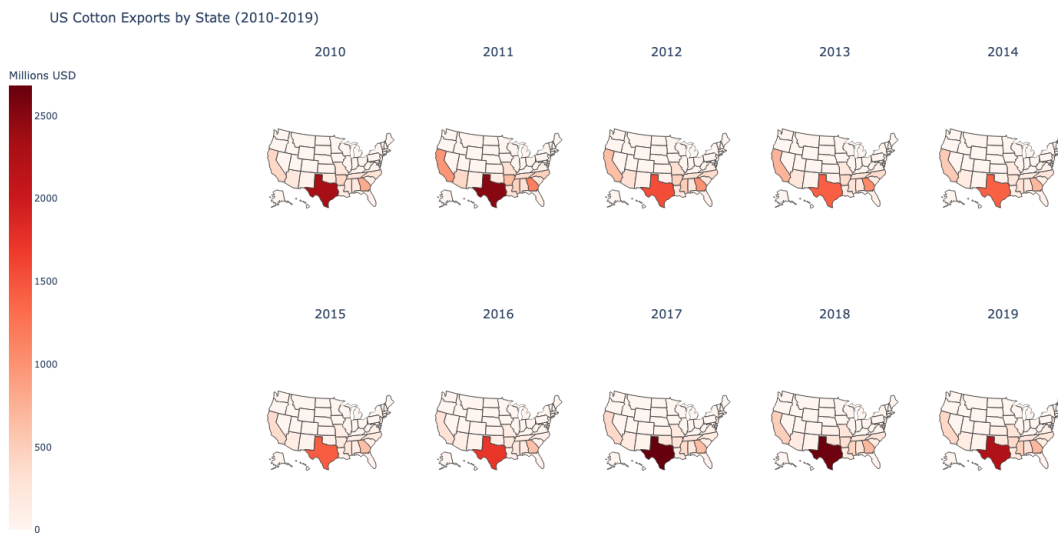


Figure 7
US Wheat Exports by State (2010-2019)

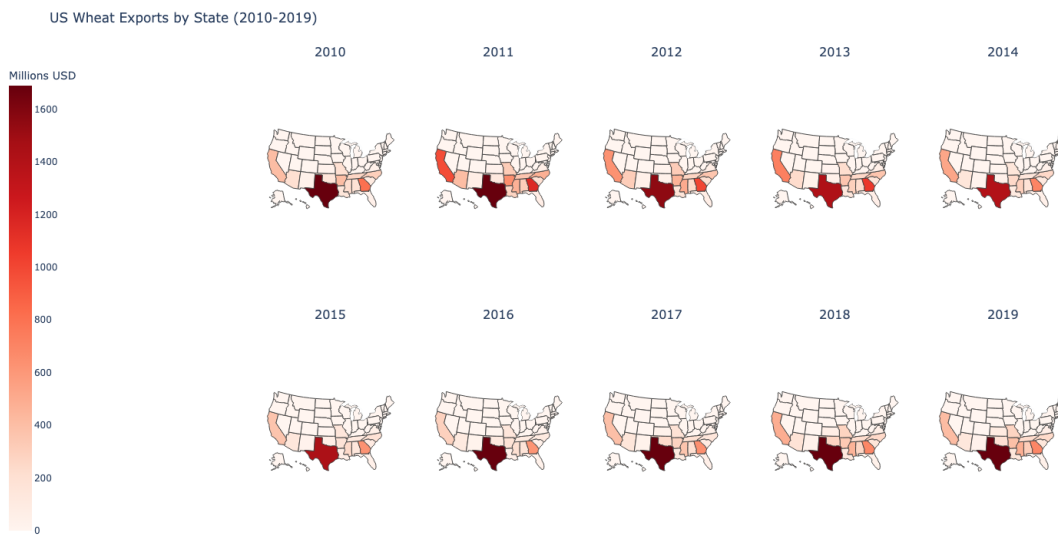


Figure 8
US Tree Nuts Exports by State (2010-2019)

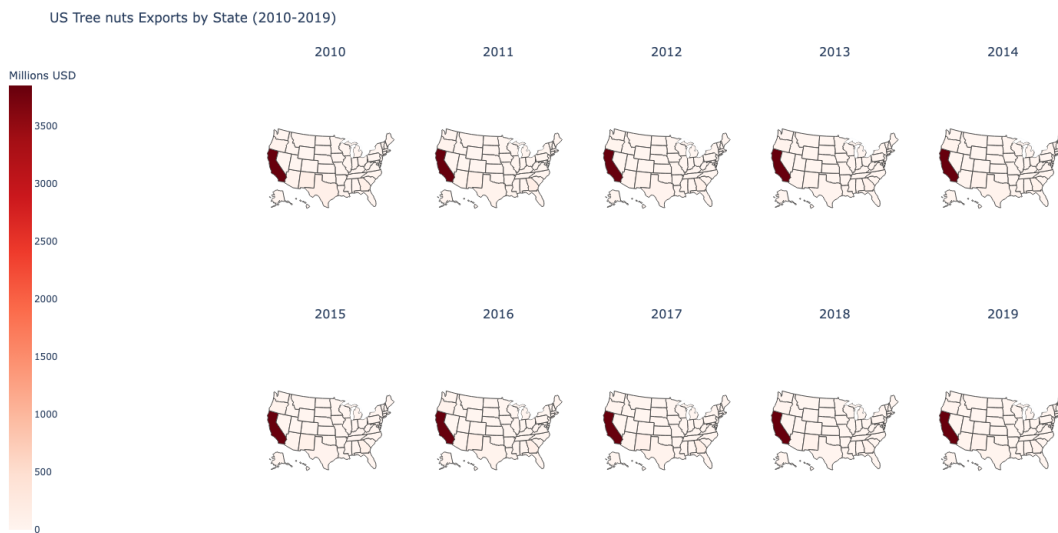
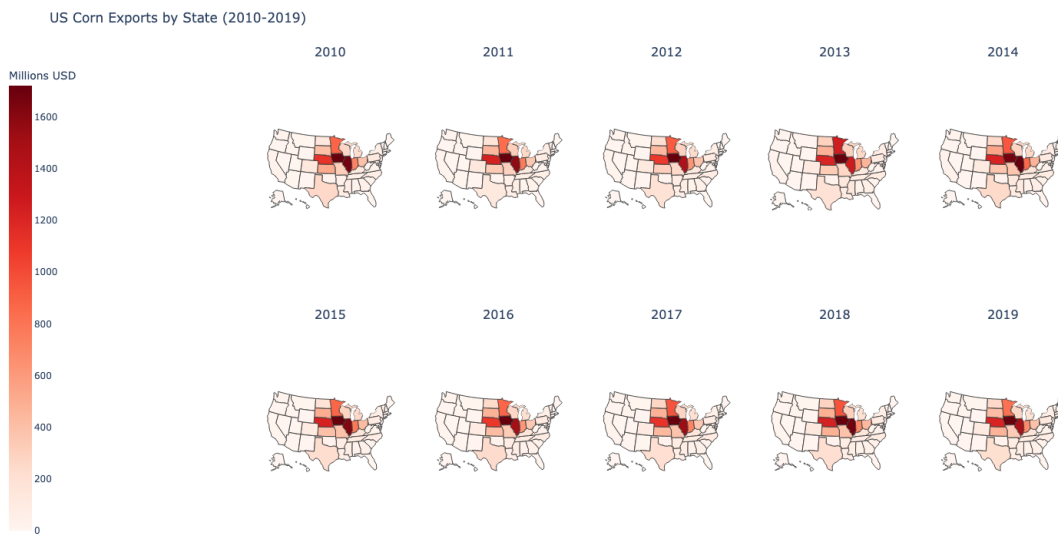


Figure 9
US Corn Exports by State (2010-2019)



10.2 Results of Event Study Analysis

Figure 10

Event Study Analysis for Aggregate Agricultural Exports (2018-2019)

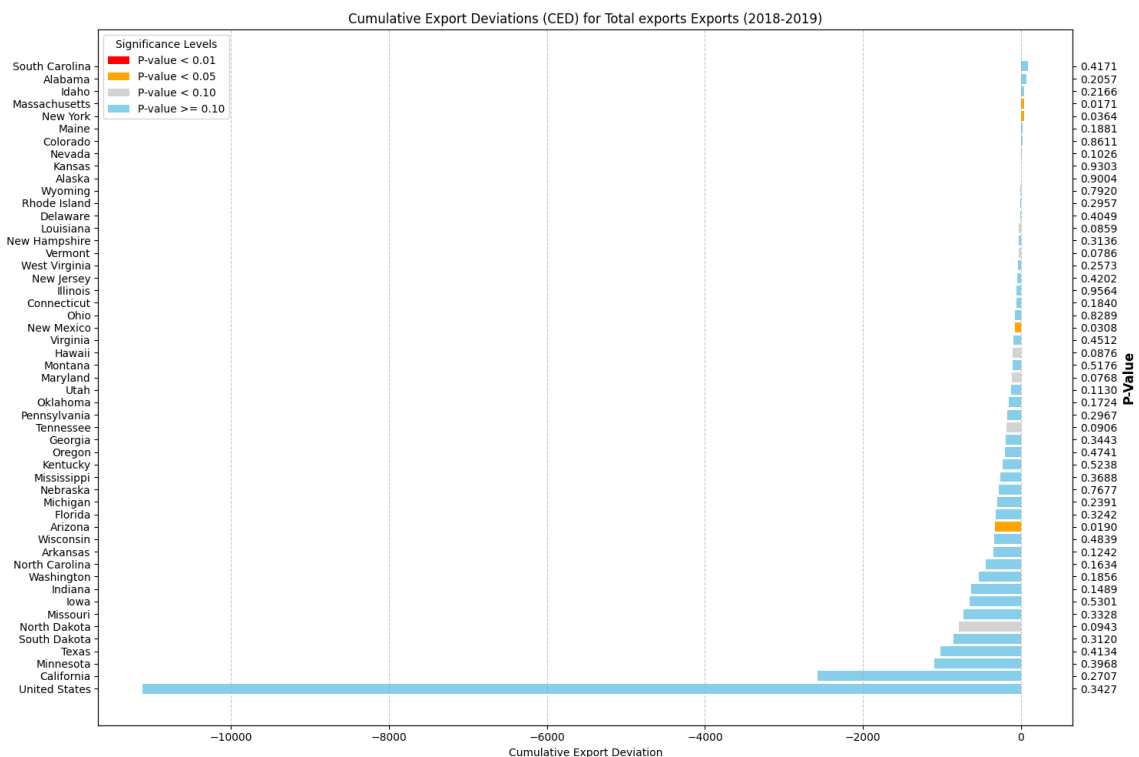


Figure 11
Event Study Analysis for soybean Exports (2018-2019)

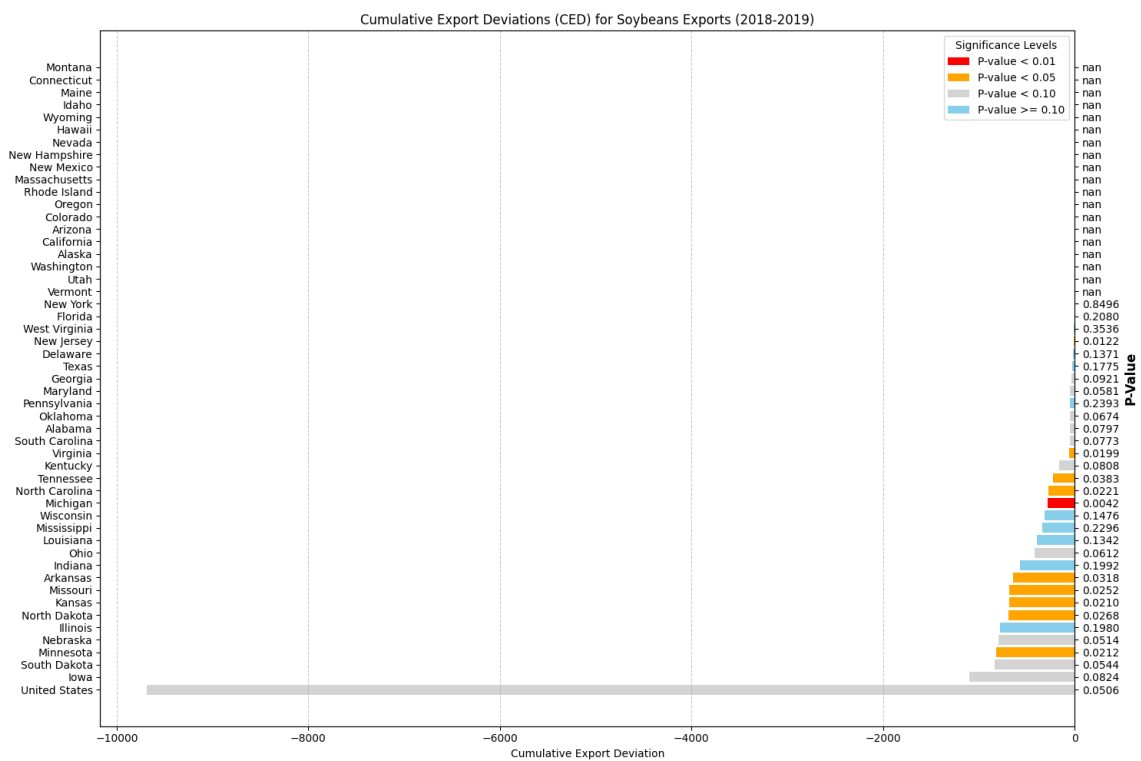


Figure 12
Event Study Analysis for Fresh Fruits Exports (2018-2019)

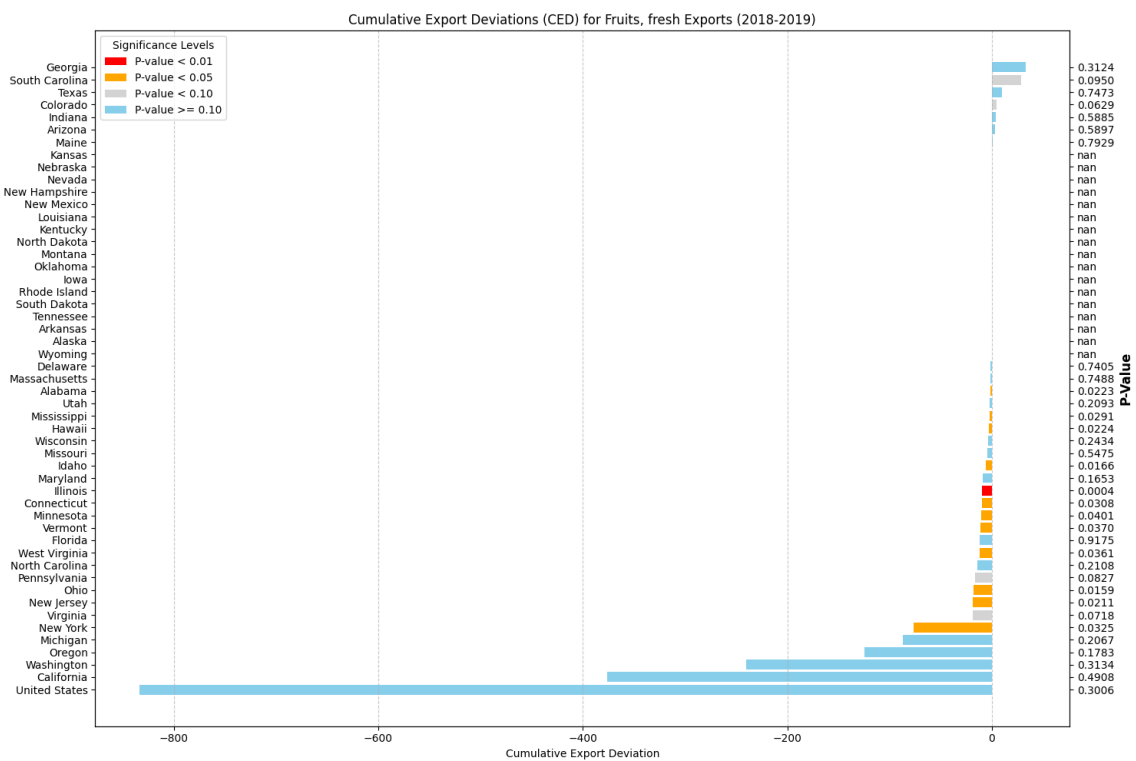


Figure 13
Event Study Analysis for Processed Fruits Exports (2018-2019)

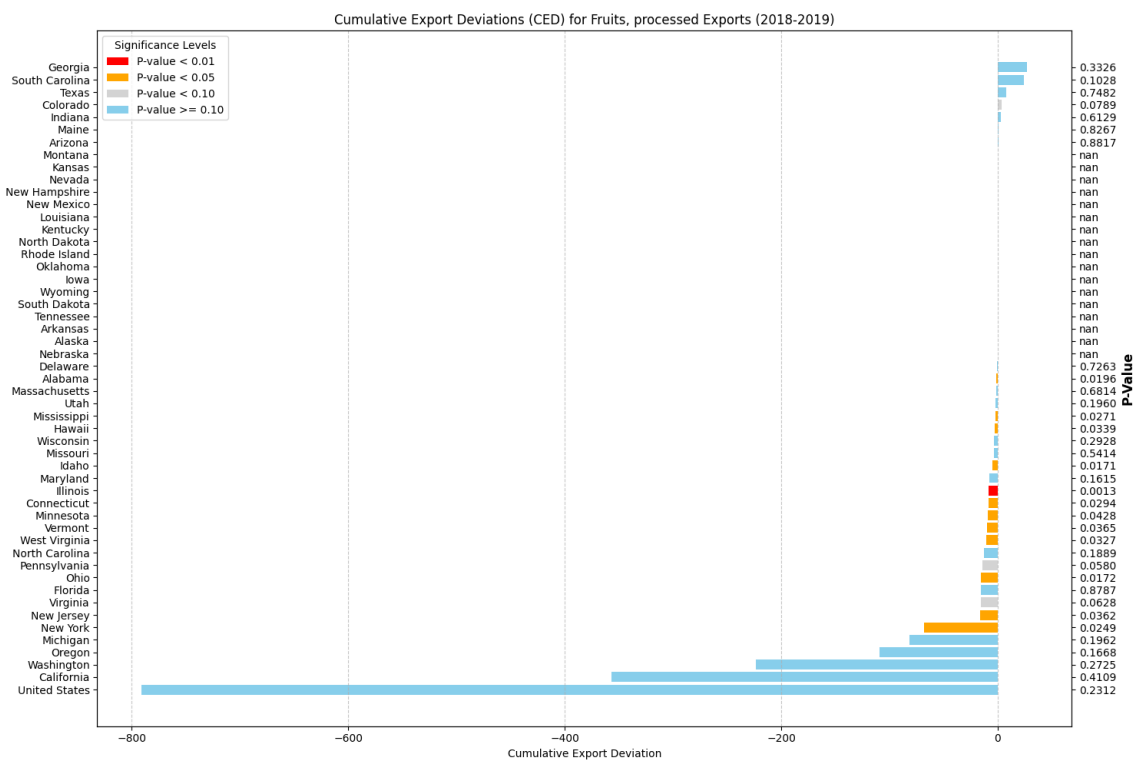


Figure 14
Event Study Analysis for Dairy Products Exports (2018-2019)

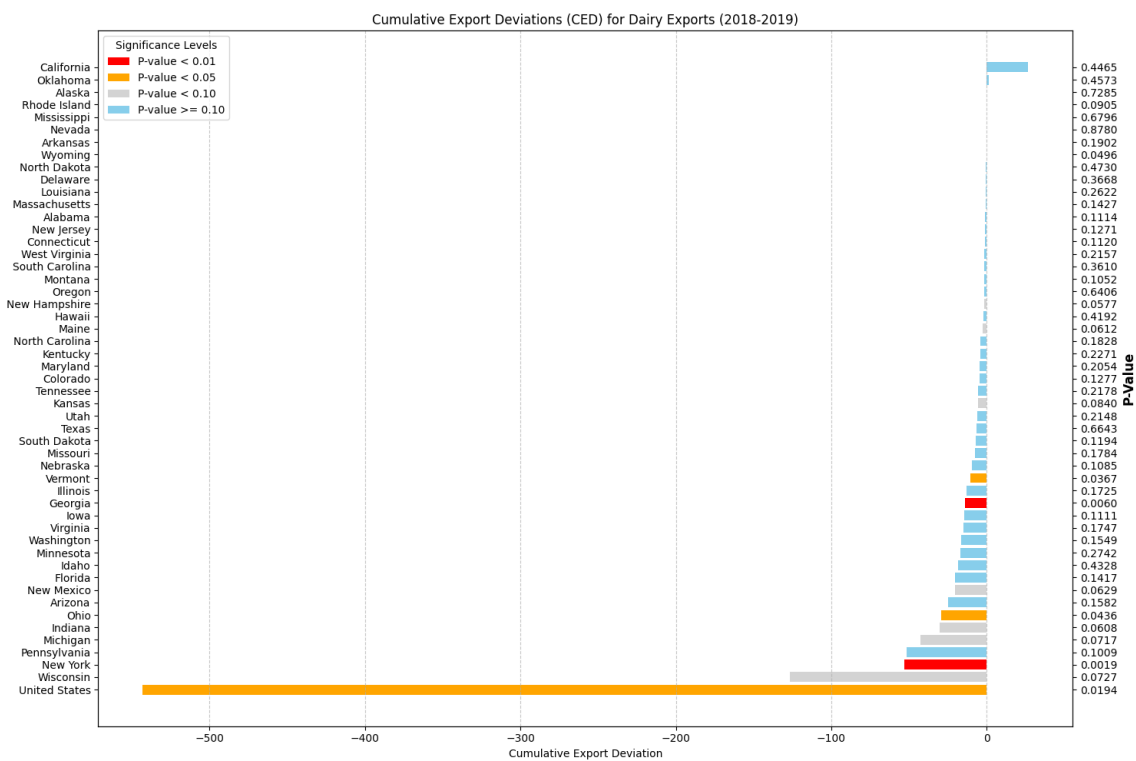


Figure 15
Event Study Analysis for Wheat Exports (2018-2019)

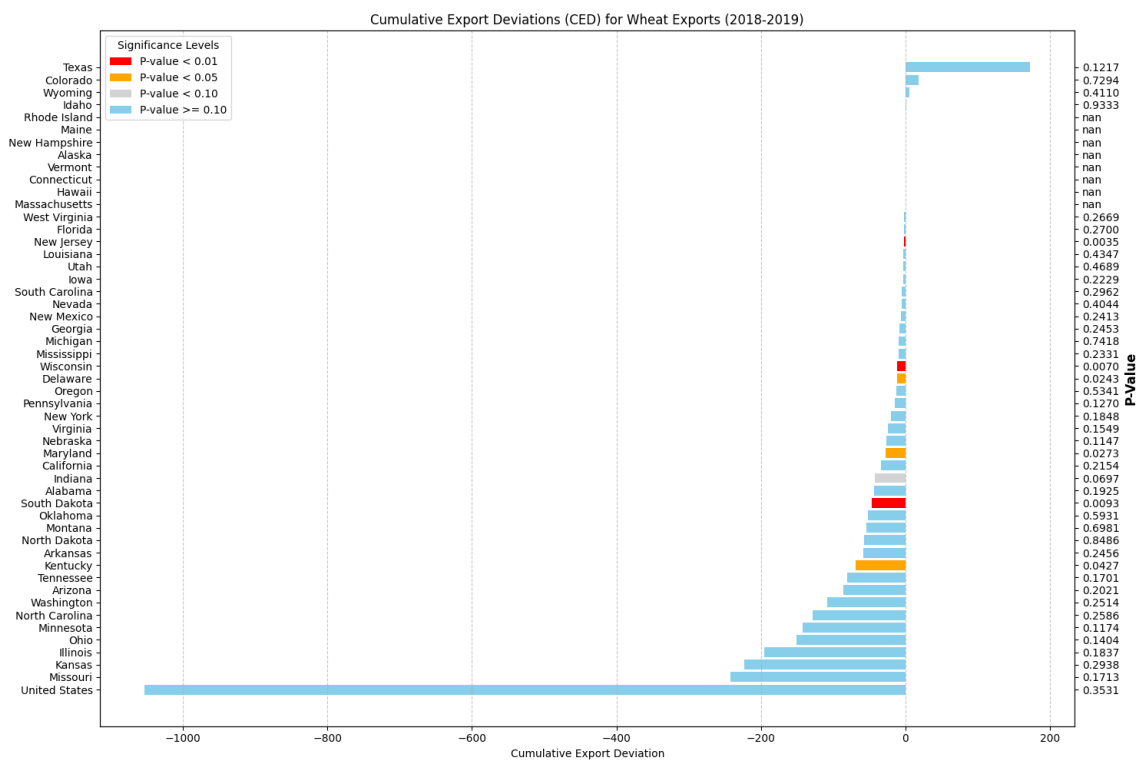


Figure 16
Event Study Analysis for Tree Nuts Exports (2018-2019)

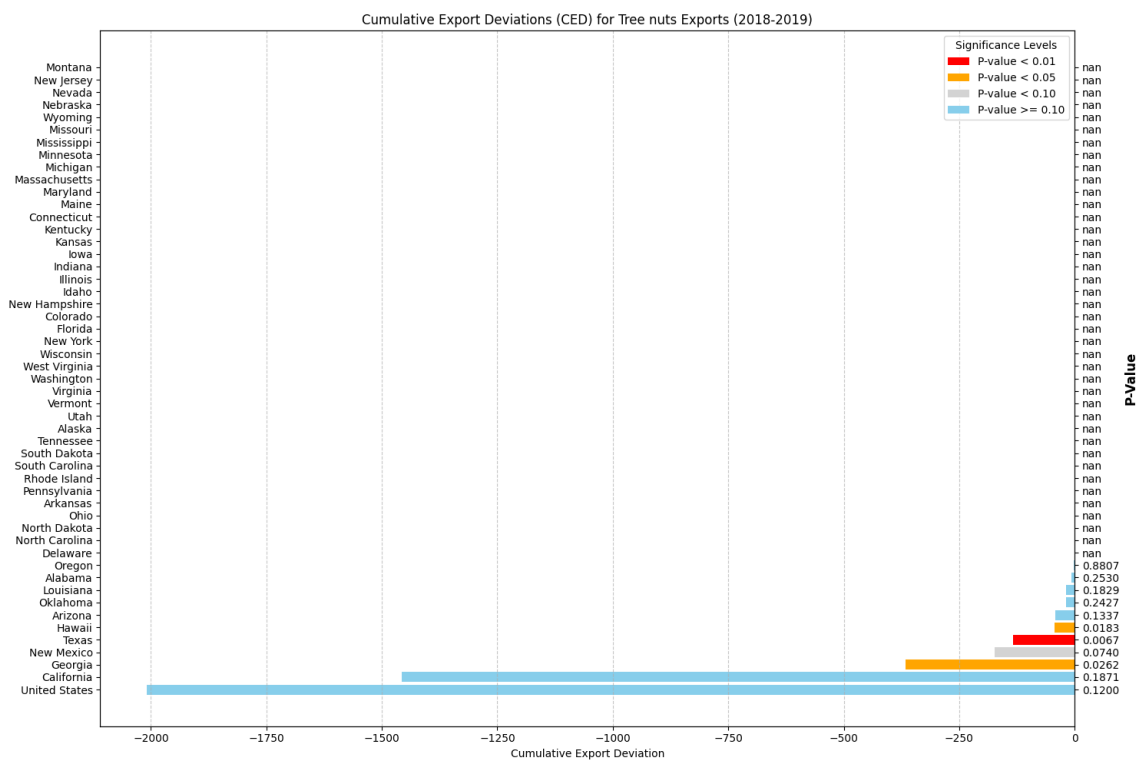
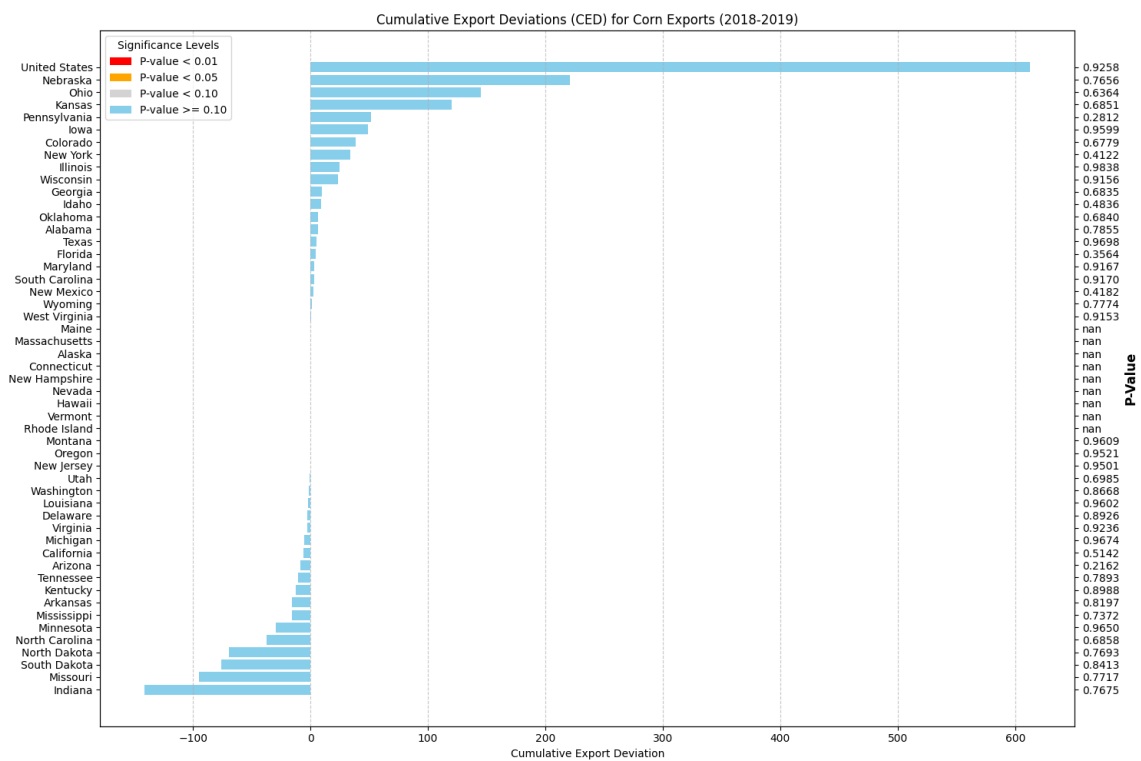


Figure 17
Event Study Analysis for Corn Exports (2018-2019)



10.3 Results from BSTS Analysis

Figure 18

BSTS result plot for Soybean Exports (2010-2019)

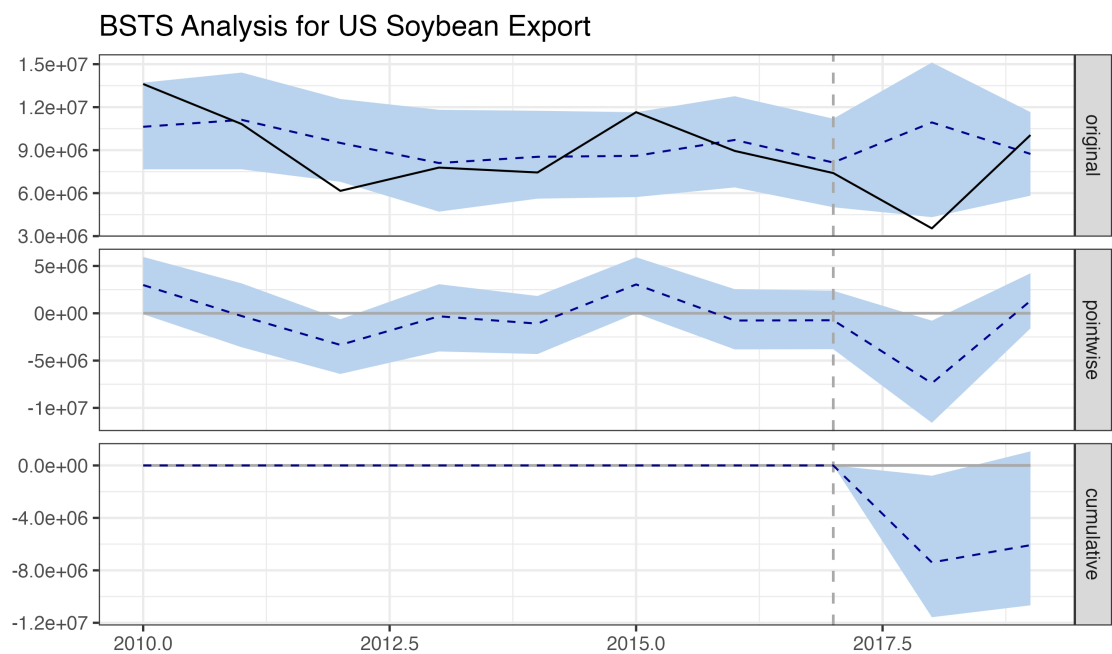


Figure 19

BSTS result plot for Soybean Exports without Brazil in the Control group (2010-2019)

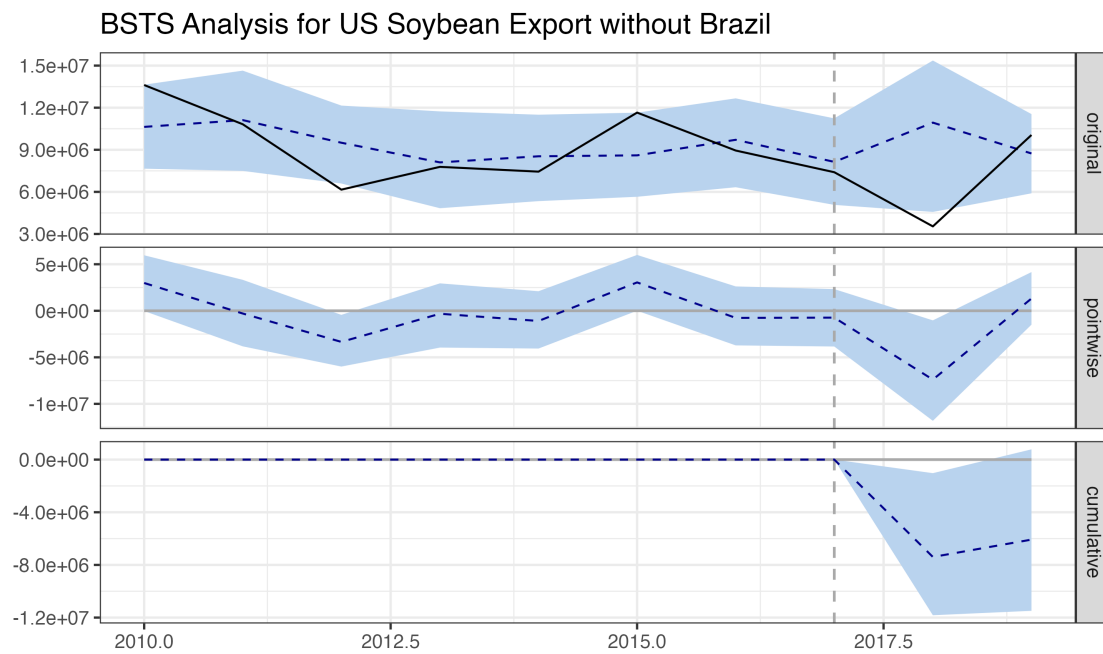


Figure 20
BSTS result plot for Sorghum Exports (2010-2019)

