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The 2021 Container Shipping Crisis and its Consequences for US Agricultural Exports

Colin A. Carter, Sandro Steinbach, and Xiting Zhuang

Address for correspondence: Sandro Steinbach, Center for Agricultural Policy and Trade Studies, Department of Agribusiness and Applied Economics, North Dakota State University, Richard H Barry Hall 400, Fargo, ND 58108, USA (sandro.steinbach@ndsu.edu). Colin A. Carter is at the Department of Agricultural and Resource Economics, University of California, Davis, USA. Xiting Zhuang is at the Department of Agricultural and Resource Economics, North Dakota State University, USA.

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Abstract

This study examines the impact of the 2021 container shipping disruptions on US agricultural trade, utilising a non-linear panel event study methodology and detailed port-level trade data. We find that US containerised agricultural exports were 22 per cent lower than anticipated from May 2021 to January 2022, resulting in a considerable export loss of about USD 10 billion. Our analysis highlights regional and product-specific variations in trade effects, with ports in the Western and Southern USA experiencing the most severe impacts. We also document considerable treatment heterogeneity according to the customs region, export destination, freight costs, and local labour shortages.

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1.0 Introduction

The coronavirus pandemic had considerable implications for global food supply chains (Garnett *et al.*, 2020; Hobbs, 2021). Disruptions to food production, processing, and shipping caused a breakdown of just-in-time supply chains, with adverse consequences for food security (Laborde *et al.*, 2020). The USA experienced substantial domestic and international adjustments in food supply (Arita *et al.*, 2021; Beckman and Countryman, 2021; Chenarides *et al.*, 2021). Arita *et al.* (2022) found that global agricultural and food trade in 2020 was 7 to 9 per cent below the counterfactual level. As a result of increased unemployment benefits, stimulus payments, and deferred consumption expenditures, the US personal saving rate increased considerably in the second half of 2020, reaching 27 per cent in March 2021 (Carroll *et al.*, 2020; Coibion *et al.*, 2020). The excess saving of USD 2.3 trillion contributed to a spending spree on durable goods met by a considerable expansion of imported goods in containers (Parker *et al.*, 2022). US ports, especially on the West Coast, could not keep up with the additional containerised imports. Over 100 loaded vessels were stranded off the Southern California coast in November 2021, leading to considerable port congestion and shipping delays.

The shipping container turnaround time at US ports was considerably increased in 2021. For instance, California container ports took almost twice as long to handle incoming cargo compared to the previous year. These disruptions meant empty containers became more valuable in Asia, so freight companies sent back more empty containers instead of filling them with agricultural products (Carter *et al.*, 2021). As a result, in January 2022, 66 per cent of all containers exported from US ports were empty. This share increased considerably from 46 per cent in 2019. Simultaneously, container freight rates from Asia to the USA increased sixfold, while those on the backhaul route to Asia almost tripled (Bloomberg, 2023). Similar freight rate increases were observed for other US ports. As a result, US agricultural exporters faced increasing difficulties accessing empty containers and shipping agricultural products abroad, resulting in increased domestic inventories for many agricultural goods.[1]

This paper measures the impact of global container shipping disruptions on US containerised agricultural exports. We rely on a panel event study approach that allows for dynamic lags and leads relative to the event of interest and controls for unobserved factors potentially correlated with the treatment through high-dimensional fixed effects. This flexible specification of the fixed effects enables us to account for shocks resulting from unobserved changes in the demand and supply patterns at the port-destination-product level. Since exports from other countries or different product categories could also be affected by shipping disruptions, we cannot rely on such a comparison group to construct a reliable counterfactual for statistical inference. Therefore, as the control group, we used the US containerised agricultural exports at the port-destination-product level from 2014 to 2017. This choice allows us to measure the treatment effects based on a comparison group with similar pre-trends and seasonality patterns at the port-destination-product level. We centre the event study around May 2021 because global container shipping disruptions had become a considerable

[1]Most agricultural producers are not directly involved in foreign markets, relying on intermediates and freight forwarders for exports (Saeed, 2013). In addition, some agricultural industries are characterised by considerable market concentration in export markets. Schweizer *et al.* (2022) found that the two largest meat processors account for more than 50 per cent of the meat exports. These agricultural exporters tend to be considerably larger than the agricultural producers focused on domestic markets (Bernard *et al.*, 2005).

issue that month. The empirical approach enables us to capture pre-trends and investigate treatment dynamics in the post-event period.

Our baseline results suggest that the volume of US containerised agricultural exports was 22 per cent below the counterfactual from May 2021 to January 2022. This treatment effect translates into a loss of 740,000 20-foot container equivalent units (TEUs) exported. The adverse trade effects peaked in November 2021, when US containerised agricultural exports fell short by 130,000 TEUs, resulting in US-wide export losses of about USD 10 billion from May 2021 to January 2022. We applied several robustness checks to ensure the validity of these results. Our heterogeneity analysis nuances the baseline findings by documenting differences in the trade effects across geographic regions and product groups. US ports in the West and South were the most adversely affected and recorded, with USD 6.5 billion and USD 2.5 billion, respectively, the majority of those export losses. We find that US exports to Asian countries decreased the most. Our analysis reveals large export losses for meat, edible fruits and nuts, oilseeds, and animal feed. For some products, the trade losses from global container shipping disruptions were far more extensive than those experienced during the 2018 China–US trade war. The analysis also shows that severe labour shortages, particularly in West Coast states like California, led to significant trade disruptions, while states with minimal shortages faced lower impacts. Additionally, substantial increases in freight rates, especially from Gulf ports, were closely associated with larger post-event trade effects, underscoring the critical role of logistics and transportation costs in the disruptions observed in 2021.

The paper provides three distinct contributions to the growing literature on the trade effects of the coronavirus pandemic and global container shipping disruptions. First, we are the first to quantify the adverse trade effects of global container shipping disruptions on US containerised agricultural exports.[2] Previous ex-post studies on the trade effects of the coronavirus pandemic are limited to 2020 (for example, Arita *et al.*, 2021; Verschuur *et al.*, 2021a, 2021b; Arita *et al.*, 2022). These studies provide evidence for adverse trade effects in the vicinity of 7 to 9 per cent for global agricultural trade, and reveal considerable heterogeneity across export destinations and product categories. Espitia *et al.* (2022) provide support for considerable treatment heterogeneity along the lines of the results presented in this paper. Carter *et al.* (2023) provide an initial quantitative assessment of the trade effects caused by global container shipping disruptions focused on California ports, showing evidence of trade destruction of about USD 3.1 billion from May to November 2021. These estimates align with the qualitative work by Kent and Haralambides (2022) and the US-wide assessment of the aggregated trade effects of container shipping disruptions for manufacturing products by Steinbach (2022). Hossen *et al.* (2024) added to this work by investigating the impact of surging freight rates on US containerised agricultural trade. Our paper expands on these previous studies by providing evidence of considerable treatment heterogeneity according to the customs region, export destination, freight rates, local labour shortages, and port and product characteristics. By quantifying the agricultural trade effects of container shipping disruptions and assessing the underlying mechanisms, this study provides crucial insights for federal and state policy-makers aiming to improve the resilience of US agricultural exports to maritime transportation shocks.

[2]Note that the welfare implications of container shipping disruptions are likely heterogeneously distributed. Agricultural supply is inelastic in the short run, implying that the welfare impact could be smaller than the pure trade effects. At the same time, recent end-of-season inventories for major export-oriented commodities, such as almonds and walnuts, are at an all-time high – putting pressure on domestic prices and causing high storage costs (Carter and Steinbach, 2022).

Second, this paper speaks to the growing literature concerned with the dynamic response of international trade flows to trade shocks by using high-frequency trade data, event study methods, and high-dimensional fixed-effect models. An expanding literature documents bias in standard two-way fixed effects (TWFE) linear regression models, particularly in the presence of treatment heterogeneity across time and treated units (for example, Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2022). Such concerns are amplified in the presence of diverging trends among treated and untreated units (Freyaldenhoven *et al.*, 2019; Marcus and Sant'Anna, 2021). These biases extend to the international trade literature with its focus on the response to trade policy shocks, which are often characterised by many treatment dynamics over time (for example, Amiti *et al.*, 2021; Malgouyres *et al.*, 2021; Ding *et al.*, 2022; Ahn and Steinbach, 2022; Steinbach, 2022). For instance, ignoring the temporal heterogeneity and potential pre-trends can miss the 'true' trade effects of global container shipping disruptions (Attinasi *et al.*, 2022). By developing an event study method for non-linear gravity-type regression models with high-dimensional fixed effects, we contribute a novel perspective on measuring the dynamic response to trade shocks. These insights could be beneficial for other empirical studies in the trade realm concerned with trade policy shocks, such as research on the trade effects of regional and multilateral trade integration and preferential trade provisions (for example, Grant and Lambert, 2008; Grant and Boys, 2012; Breinlich *et al.*, 2021; Arita *et al.*, 2022; Curzi and Huysmans, 2022; He, 2022).

Third, we contribute to the empirical literature measuring the impact of trade shocks with limited information on differences in the treatment intensity across cross-sectional units. Since there is little previous work on how susceptible trade flows are to global container shipping disruptions, one cannot use trade flows of untreated varieties (port-destination-product triples) to measure the causal treatment effects (Carter and Steinbach, 2020; Fajgelbaum *et al.*, 2020, 2021). Instead, we developed a novel empirical strategy that relies on high-dimensional fixed effects combined with high-frequency trade flows from untreated temporal units. The fixed effects allow us to account for unobserved changes in the demand and supply patterns specific to port-destination-product triples. We find strong empirical evidence that variation from previous untreated periods within the same port-destination-product triples can serve as a reliable control group (Freyaldenhoven *et al.*, 2021). Our empirical work is in line with Grant *et al.* (2021) and Arita *et al.* (2022), who used a similar research design to evaluate the trade effects of the 2018 China–US trade war and COVID-19.

2.0 Drivers of Container Shipping Disruptions

Various demand, supply, and transport cost factors contributed to global container shipping disruptions.[3] Figure A.1 shows trends in the five primary drivers.[4] First, increased unemployment benefits, stimulus checks, and deferred consumption expenditures grew the US personal saving rate in 2020 (Carroll *et al.*, 2020; Coibion *et al.*, 2020). As shown in panel (a), the personal saving rate peaked in April 2020 at 34 per cent. It remained above 14 per cent until September 2021, when the rate returned to the pre-pandemic level. In response to the fading pandemic, households

[3]Although additional factors likely contributed to US container trade disruptions, we focus on the five primary factors that caused the observed trade patterns. Some of these factors are strongly correlated. Hence, we abstain from attributing the trade effects to a particular factor as the sole explanatory variable.

[4]All figures and tables labelled with an 'A' are available in the Online Appendix: https://tinyurl.com/ysd98j6j.

released more than USD 2.3 trillion in excess savings from spring 2021 onwards (O'Trakoun, 2021). Growing earnings in most sectors exerted additional pressure on supply chains (Bell *et al.*, 2021; Domash and Summers, 2022). The increasing demand for durable goods contributed to more than 14 per cent of import demand growth in 2021 compared to the previous year. The majority of these additional imports arrive via container ships in the USA (Carter *et al.*, 2021). This import growth was heterogeneous across geographic regions, with West Coast ports asked to handle the majority of additional imports arriving from Asia. Western ports became increasingly overwhelmed by the growing imports in the spring of 2021. Various factors led to the large queue of ships on the West Coast. To name a few, pandemic-induced labour headwinds at the ports, slow chassis turns, a lack of container staging space, slow rail service, and containers out of position in the network provided some of the biggest impediments to throughput. The struggling Western ports are confirmed by the results of the World Bank's Container Port Performance Index, which investigated the performance of 351 ports worldwide (World Bank and IHS Markit, 2022). The study ranked Oakland at 334, closely followed by Los Angeles (337) and Long Beach (342), which puts California ports behind most other container ports.

Second, the growing demand for goods from Asia and the slowed turnaround times resulted in a substantial increase in maritime freight rates, as panel (b) shows. Container freight rates from Asia to the USA increased sixfold, reaching more than USD 5,000 per TEU in January 2022 (Bloomberg, 2023). At the same time, freight rates on the backhaul route to Asia increased to about USD 600 per TEU starting in May 2021, almost tripling compared to the previous year. This shipping rate differential made it more profitable for containers to be sent back to Asia empty instead of waiting several days to fill with agricultural products, or be moved up to Oakland from Los Angeles and Long Beach. Third, the timeliness of shipments decreased considerably. While the average shipping time on the transpacific westbound route was less than 50 days in 2019, the length of the journey skyrocketed starting in spring 2021 – reaching more than 110 days in January 2022, as shown in panel (c).

Fourth, the number of available containers diminished considerably, as shown by the container availability index in panel (d). The index measures the movement of full containers through US ports. A value of 0.5 means that the same number of containers leave and enter the USA in a month. The index provides evidence for a considerable shortage of export containers. The index dropped below 0.3 after May 2021, indicating more demand for export containers than total containerised imports, resulting in increased container rental fees and delayed cargo acceptance. In addition, demurrage and storage fees paid by exporters increased substantially, forcing some agricultural exporters to re-route containers through Texas, Vancouver, or the East Coast at a great expense. Fifth, these trends are reflected in the number of empty shipped containers out of US ports, as panel (e) shows.[5] Many shippers decided to cancel contracts and refused to supply empty containers to US exporters, returning them unfilled to Asia instead. As a result, the share of empty containers increased by almost 10 per cent since May 2021, reaching an all-time high of 66 per cent in January 2022. This share was considerably higher for California ports, with almost 80 per cent of exported containers shipped out empty in November 2021.

The observed interplay of port productivity, demand, supply, and transport cost factors contributed to global container shipping disruptions, and meant that containerised agricultural

[5]Figure A.2 shows containerised agricultural exports by census region and major US ports. Containerised shipments in 2021 contracted 9 per cent compared to 2019, with Western ports driving this effect. California ports handled 42 per cent of containerised shipments in 2021. Their share in overall containerised agricultural exports has grown by 1 per cent since 2019.

exports fell considerably in 2021. Aggregate trade data show that agricultural exports fell from a high of more than 300,000 TEUs in November 2020 to less than 200,000 TEUs in January 2022, as shown in panel (f) of Figure A.1. Compared with May 2021, agricultural exports were about 15 per cent lower in January 2022. At the same time, as shown in Figure A.3, containerised agricultural imports contracted only slightly, falling by 6 per cent from November 2020 to January 2022. In contrast, the contraction of non-agricultural imports was more substantial, indicated by a reduction of containerised imports of 12 per cent during the same period. These adverse trade effects vary considerably between geographic regions and product groups.

3.0 Methods and Data

3.1 Empirical approach

We rely on a panel event study approach to assess the dynamic treatment effects of global container shipping disruptions on containerised agricultural exports from US ports. The baseline model allows for dynamic lags and leads relative to the event of interest. It controls for unobserved factors potentially correlated with the treatment through high-dimensional fixed effects. The event study design enables us to capture pre-trends and investigate treatment dynamics in the post-event period (Schmidheiny and Siegloch, 2020; Freyaldenhoven *et al.*, 2021; Roth and Sant'Anna, 2021). For the baseline analysis, we adopt a non-linear panel regression model for count data, with dynamic treatment effects specified as follows:

$$y_{ijst} = \exp\left(\alpha_{ijs,mo} + \alpha_{ijs,yr} + \sum_{k=-8}^{8} \beta_k r_{ijs,t-k}\right)\epsilon_{ijst}, \tag{1}$$

where we denote the port with i, the foreign destination with j, the product with s, the time with t, the event year with yr, and the event month with mo. We define the outcome variable with y_{ijst} and study four primary outcomes; namely, the free on board (FOB) export value (in USD), TEUs exported, quantity (measured either as count or in kilograms), and unit value (defined as the value divided by the quantity).[6] The model indicates fixed effects at the port-destination-product-month level with $\alpha_{ijs,mo}$ and the port-destination-product-year level with $\alpha_{ijs,yr}$. The fixed effects account for unobserved factors that vary at the port-destination-product level and could confound the relationship of primary interest. They are flexible over time (month and year) because multiple factors that likely vary within and across years determine product demand, supply, and trade costs for agricultural products. This specification of the time-fixed effects enables us to account for shocks resulting from unobserved changes in the demand and supply patterns at the port-destination-product level (Jochmans, 2017; de Chaisemartin and D'Haultfoeuille, 2022). For instance, most agricultural commodities exhibit seasonality patterns in export volumes. Moreover, the port-product-time fixed effects also account for other time-variant factors that are unobserved, predictive of the outcome, and potentially correlated with the treatment. For instance, port infrastructure, freight rates, and anchor time are such characteristics (Clark *et al.*, 2004; Jacks and Pendakur, 2010; Korinek and Sourdin, 2010; de Soyres *et al.*, 2020).

[6]We include TEU in the analysis because it provides critical insight into how disruptions affect the overall flow of shipments, allowing us to examine bottlenecks and capacity constraints within the supply chain.

The term $\sum_{k=-8}^{8}\beta_k r_{ijs,t-k}$ measures the dynamic treatment effects of global container shipping disruptions on containerised agricultural exports from US ports.[7] The baseline regression model is flexible to some degree; that is, it allows the treatment effect to be dynamic before and after the first reported supply chain issues. Therefore, the dynamic treatment model can account for the severity of the supply chain bottlenecks and quantify the treatment intensity relative to the event month. We centre the event study around May 2021 because port congestion and container shortages became a major bottleneck that month.[8] Following standard practice in the event study literature (Freyaldenhoven *et al.*, 2021), we use a symmetric event window that extends eight months before and after the event. This approach allows us to account for potential pre-trends and delays in trade data reporting and quality.

The regression specification addresses level differences in export volumes between products and export destinations through the port-destination-product fixed effects. We deploy the parsimonious assumption that all latent confounders are invariant at the port-destination-product-event-month and port-destination-product-event-year levels, and thus captured by $\alpha_{ijs,mo}$ and $\alpha_{ijs,yr}$. To account for these fixed effects and identify the treatment effects of global container shipping disruptions, we require a control group that has the same trends in the pre-treatment period and is not affected by global container shipping disruptions. Since we cannot rely on trade data from other countries or product categories to construct a reliable counterfactual at the port-destination-product level, we resort to US containerised agricultural exports at the port-destination-product level from 2014 to 2017 as the control group. This choice allows us to measure the causal treatment effects based on a comparison group with similar pre-trends at the port-destination-product level.[9] Our identification strategy draws on Arita *et al.* (2022) and Steinbach (2023), who used a similar research design to evaluate the trade effects of the coronavirus pandemic and the Russian invasion of Ukraine. We denote the multiplicative error term with ϵ_{ijst}.

The outcome variable y_{ijst} represents the non-negative integer count of containerised agricultural exports at the port-destination-product level. One approach to identifying the relationship of interest would be to transform the outcome variable and parameters using a linear regression model. However, this approach would be inappropriate as our outcome is a count. A linear regression model cannot identify the relationship of primary interest because it cannot ensure the positivity of the predicted values of the count outcome (Wooldridge, 1999; Cameron and Trivedi, 2013). The discrete nature of the outcome makes it difficult to find a transformation with a conditional mean that is linear in parameters. Heteroskedasticity could exaggerate this issue further as the transformed errors could be correlated with the covariates. Such correlation can result in an inconsistent identification of the treatment effects. Thus, even if the transformation of the conditional mean is correctly specified, obtaining unbiased estimates of the relationship would be difficult. Therefore, we directly model the relationship of interest between containerised agricultural exports and the treatment variables to account for this issue.

[7]Because the treatment is not staggered, potential heterogeneity across treated and untreated units over time is not a concern for our identification design (Borusyak *et al.*, 2024).

[8]This choice is informed by the observed changes in demand, supply, and transport cost factors, as described in Section 2. While some of those factors could vary at the port-destination-product level, the choice of fixed effects addresses these omitted variable concerns by including event year and month shifters at the port-destination-product level, and estimating dynamic treatment effects.

[9]We conduct several robustness tests to check the validity of the comparison group choice that is discussed in Section 4. These robustness checks confirm the validity of the empirical approach.

We ensure the positivity of the covariates by employing a non-linear regression model that uses an exponential form equation.

We follow common practice in the international economics literature, and rely on the Poisson pseudo-maximum likelihood (PML) estimator to identify the relationship between the count outcome and the treatment variables (Gong and Samaniego, 1981; Gourieroux *et al.*, 1984). Even if the conditional variance is not proportional to the conditional mean, the estimator is unbiased and consistent in the presence of heteroskedasticity (Wooldridge, 1999; Cameron and Trivedi, 2013). A further advantage of the Poisson PML estimator is that the scale of the dependent variable does not affect the parameter estimates and that the estimator allows us to deal with zero trade flows consistently (Silva and Tenreyro, 2006). As shown in Table A.1, the share of zero observations is considerable at the port-destination-product level. We follow standard practice, rely on a linear regression model for the unit value specification, and apply a log transformation of the outcome (Kuck and Schweikert, 2023). We account for the high-dimensional fixed effects by using a modified version of the iteratively re-weighted least-squares algorithm that is robust to statistical separation and convergence issues (Correia *et al.*, 2019, 2020). Because the standard errors could be correlated at the port-destination-product level, we follow standard practice in the trade literature and cluster them at this level (Cameron and Miller, 2015; Weidner and Zylkin, 2021).[10]

3.2 Data

We sourced export data for all US ports from the United States Census Bureau (2023), measuring monthly exports for all US ports and export destinations. In addition to the export value and shipping volume, the data set includes information on the transport mode (air, bulk vessels, and containerised vessels). We aggregated the trade data at the HS subheading (six-digit) level from September 2014 to January 2022. We supplemented this data set with bills of lading for all US ports from the Port Import/Export Reporting Service (PIERS) (IHS Markit, 2023). PIERS covers all waterborne cargo vessels that enter and exit US ports. This data is sourced directly from the US Customs and Border Protection, averaging about 75,000 reported transactions per day. We used the transaction-level data to construct a monthly account of containerised agricultural exports measured in TEUs for all US ports at the HS subheading level (Flanagan *et al.*, 2021). We used the HS information to classify all products into agricultural (HS chapters 0 to 24) and other exports (HS chapters 25 to 99). After controlling for singleton observations without variation at the port-destination-product level by using the approach developed by Correia *et al.* (2020), the final balanced panel data set covers the monthly value, TEUs, and quantity shipped out of 104 US ports handling containerised agricultural products destined to 222 export destinations, and listed under 1,013 HS subheadings from September 2014 to January 2022. We use this data set to construct the event study panel. Table A.1 provides descriptive statistics for the pre-event and post-event periods. The descriptive statistics indicate a total reduction of 10 per cent and a mean reduction of 14 per cent in containerised shipments of agricultural products measured in TEUs.

[10]A potential concern is that the high-dimensional fixed effects could create asymptotic estimation bias due to the incidental parameter problem. We applied the correction method proposed by Weidner and Zylkin (2021) to account for this issue. This robustness check provides no support for such estimation bias at conventional levels of statistical significance. The corrected parameter estimates and standard errors for the baseline model are available upon request from the authors.

4.0 Results and Discussion

4.1 Baseline

We present the baseline event study estimates for containerised agricultural exports from US ports in Figure 1. The figure presents parameter estimates for export value, TEUs, quantity, and unit value as the outcome variables. Each subfigure plots the dynamic treatment parameters, 95 per cent confidence intervals, and uniform sup-t bands for the event-time of the outcome (Montiel Olea and Plagborg-Møller, 2019; Freyaldenhoven *et al.*, 2021). We also overlay estimates from a static model represented by the dashed red line. The notes in Figure 1 report the corresponding p-value for a Wald test. Apart from the value specification, all p-values from the static models are significant at conventional levels of statistical significance. We also conducted a Wald test for pre-event trends and anticipatory behaviour. We find no evidence of significant pre-trends for the value, TEUs, and quantity specifications.[11] However, there is consistent evidence for pre-trends in the unit value specification. Because the treatment effect could be dynamic at the endpoints of the event window, we also conduct a Wald test for the null that the treatment dynamics level off. We find limited statistical support for levelling off of the treatment effects at conventional levels of statistical significance for all outcomes.[12]

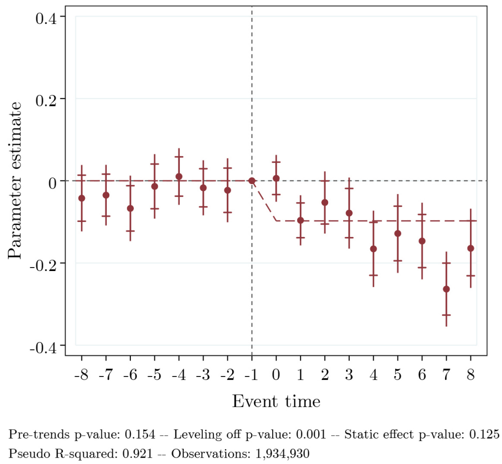
The value specification in panel (a) of Figure 1 provides evidence for gradually increasing adverse treatment effects. The average post-event treatment effect is –0.121 log points. The event coefficients are statistically significant, starting with event month 2 (June 2021). The average treatment effect increased from –0.098 log points to –0.176 log points, comparing event months 1 to 4 (June to September 2021) with event months 5 to 8 (October 2021 to January 2022) – indicating that the global container trade issues amplified in autumn 2021 and winter 2021/2. The TEU's specification in panel (b) draws a similar robust picture of adverse treatment effects for containerised agricultural exports. The average post-event treatment effect is –0.373 log points, considerably larger than that for the value specification, pointing towards positive price effects during that period. The event coefficients indicate the largest adverse treatment effects for event month 6 (November 2021). Since then, some trade recovery has been observable for the TEU's specification. However, containerised agricultural exports remained depressed at about –0.490 log points on average. The quantity specification in panel (c) draws a similar picture of gradually increasing adverse trade effects. According to that specification, containerised agricultural exports were –0.250 log points below the counterfactual during the post-event period. The adverse treatment effects increased to –0.355 log points for event months 5 to 8 (October 2021 to January 2022), pointing towards a continued disruption of containerised agricultural exports. In contrast, we find some evidence for statistically significant price effects in the unit value specification in panel (d). However, this specification is prone to estimation bias due to the unaddressed pre-trends.

[11]Since the pre-trend tests are statistically insignificant and the treatment pathways in the pre-treatment period are flat, the research design is validated. The fixed effects can accurately account for unobserved maritime shocks unrelated to the treatment but predictive of the outcome, such as the Suez Canal obstruction in March 2021 and COVID-19 disruptions in major trading partners.

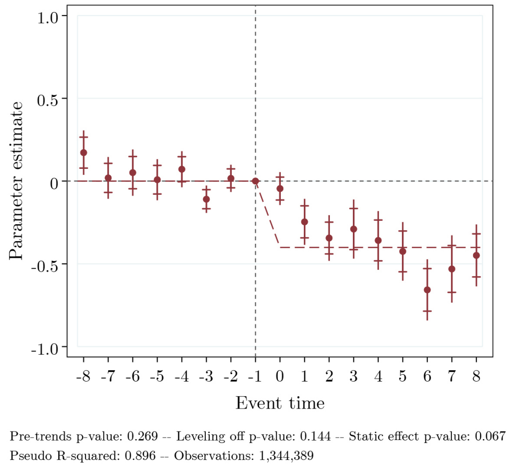
[12]Note that the observation number for the unit value specification differs from the value and quantity specifications because a linear regression model was used to identify the parameters of interest in that specification. This estimator choice implies that observations with zero unit value were not retained. In contrast, the Poisson PML estimator used for the three other specifications can include zero trade flows.

Figure 1

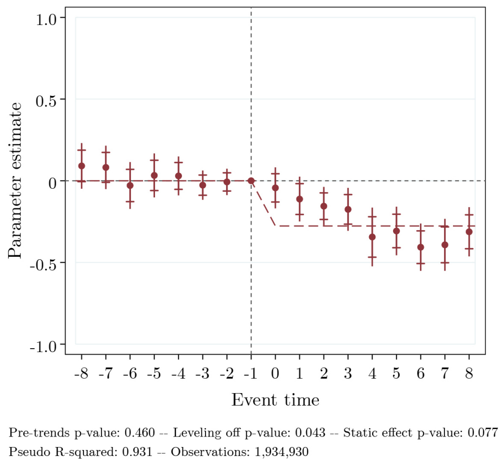
Event Studies for US Containerised Agricultural Exports



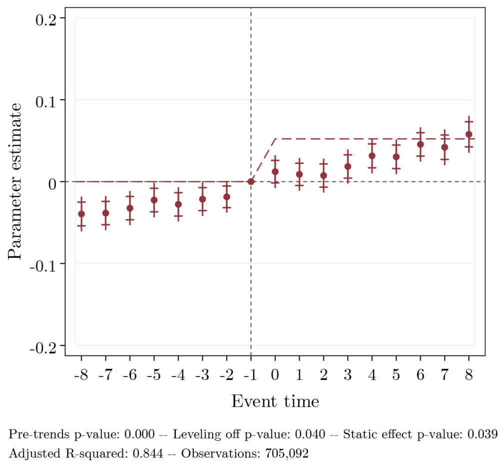
(a) Value



(b) TEUs



(c) Quantity



(d) Unit value

Note: All regressions include port-destination-product-year and port-destination-product-month fixed effects. Standard errors are adjusted for within-cluster correlation at the port-destination-product level. We plot the dynamic treatment parameters, 95 per cent confidence intervals, and uniform sup-t bands for the event-time coefficients. Results from a static model are overlaid as a dashed line. We report Wald tests for pre-trends, levelling off dynamic treatment effects, the pseudo/adjusted R-squared, and the panel size in the figure note. The event time is measured in months relative to April 2021.

We used the parameter estimates and average unit values at the port-destination-product level for the pre-event month (April 2021) to estimate the reduction in containerised agricultural exports and the associated foreign trade losses.[13] We show changes over time in Figure A.4. On

[13]We used unit values for the pre-event month because the unit value specification shows significant pre-trends. As discussed in Subsection 4.2, the unit values are not affected by global container shipping disruptions after subtracting the linear pre-trends.

average, monthly containerised agricultural exports were 83,000 TEUs below the counterfactual. These adverse trade effects peaked in November 2021, when US containerised agricultural exports fell 132,000 TEUs short. Overall, US containerised agricultural exports were 743,000 TEUs below the counterfactual from May 2021 to January 2022. The trade reduction resulted in export losses of about USD 10 billion, representing roughly 22 per cent of the overall containerised agricultural exports.[14]

4.2 Robustness

Devil's Advocate Model – A failure to reject the null hypothesis of no pre-event trends does not imply that there is no confounding variable that could threaten the identification of the 'true' treatment effects (Roth, 2022). To test for the presence of a confounding variable, we estimated a devil's advocate model, which assumes that the 'true' value of the treatment effect is zero. We identified the least 'wiggly' event-time path that is, among polynomial confounds, consistent with the estimated event-time path – the least 'wiggly' path with the lowest polynomial order (Rambachan and Roth, 2023). Panels (a) and (d) of Figure 2 compare the quantity and unit value specifications. We find that the event-time path for the quantity outcome is 'wiggly', making the existence of a confounding and unobserved variable implausible, and implying that global container shipping disruptions did causally affect US containerised agricultural exports. In contrast, we find limited evidence for a 'wiggly' event-time path in the unit value specification, raising concerns about a potential confounding variable that seems linear in event time.

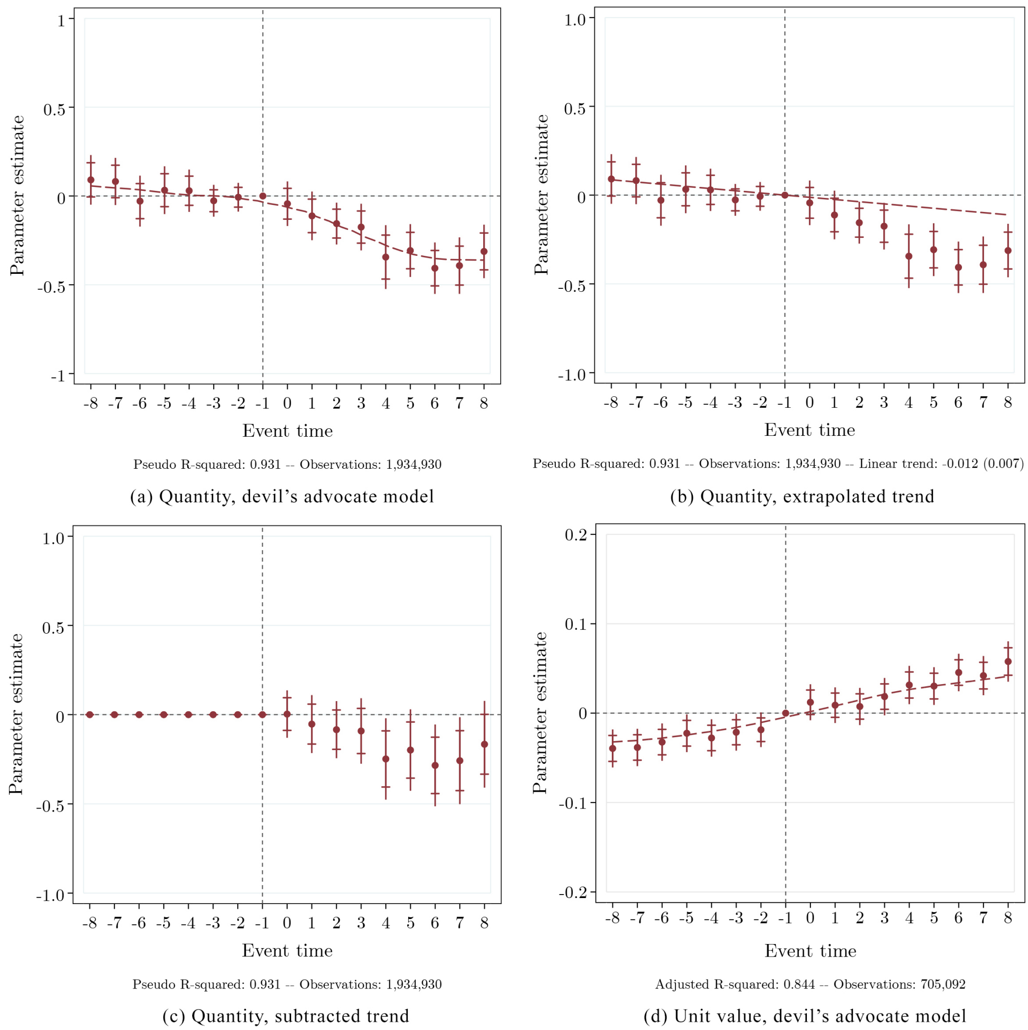
Extrapolated Linear Pre-Trends – The potential for significant pre-trends before the treatment month requires us to be cautious about the causal interpretation of the estimated trade effects (Freyaldenhoven *et al.*, 2019; Marcus and Sant'Anna, 2021). Although the dynamic treatment specification avoids downward bias from averaging over the periods before the treatment month, it also assumes that treated units would have continued on the same growth path as non-treated units after May 2021. To account for the potential impact of pre-trends, we estimate equation (1) under the alternative assumption that the linear pre-trends of targeted units would have continued on their pre-treatment paths following the approach outlined by Dobkin *et al.* (2018) and Freyaldenhoven *et al.* (2021). There are two notable differences from the baseline specification. First, only the treatment response relative to the post-event period is estimated. Second, we include a linear trend that takes the value of the monthly difference relative to the treatment month and is set to zero afterward. This specification identifies the adjusted treatment effects as the deviation between the estimated treatment effect after the treatment and the extrapolated pre-trend.

Figure 2 presents results for the linear pre-trend analysis comparing estimation results for the export quantity and unit value as dependent variables. The dotted red line in panels (b) and (e) overlays the estimated linear trend upon the baseline event study estimates from equation (1). The linearity assumption is reasonable for both outcomes as the estimated trend growth lies within the sup-t confidence intervals of the non-parametric event study estimates throughout the pre-treatment period. Next, we plot the deviation from the estimated post-event response and the extrapolated pre-trend in panels (c) and (f). The average post-event trade effects for the quantity

[14]The approach cannot speak to inventory adjustments and downward price pressure in the domestic market. Hence, the welfare effects are likely below the export losses since agricultural producers could sell some goods in the domestic market or store them. However, how large that margin of adjustment might be is difficult to assess because of the unavailability of high-frequency and product-level inventory and sales data.

Figure 2

Devil's Advocate Model and Subtracted Potential Confound from Pre-event Periods



(a) Quantity, devil's advocate model

(b) Quantity, extrapolated trend

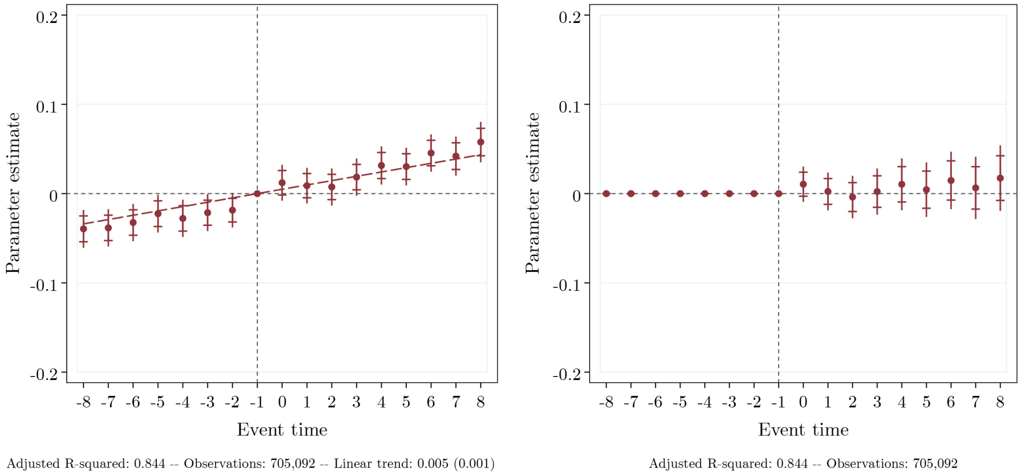
(c) Quantity, subtracted trend

(d) Unit value, devil's advocate model

specification decrease from −22.1 per cent to −12.6 per cent. However, since the estimated linear trend coefficient is insignificant at conventional levels of statistical significance, we can reject the hypothesis of pre-trends driving the observed trade effects. In contrast, we find a statistically significant linear pre-trend of 0.005 log points for the unit value specification. Subtracting that pre-trend from the estimated post-event parameter estimates implies that the average post-event trade effect becomes statistically insignificant. It falls from 2.9 per cent to 0.3 per cent, implying no evidence of significant trade effects for the unit value specification. Therefore, the remainder of the analysis will focus on export quantity as the primary outcome. Since the trend coefficient for the quantity specification is statistically insignificant, we can rule out pre-trends as the primary

Figure 2

Devil's Advocate Model and Subtracted Potential Confound from Pre-event Periods (Continued)



(e) Unit value, extrapolated trend

(f) Unit value, subtracted trend

Note: The overlaid dashed line in panels (a) and (d) shows the least 'wiggly' event-time path. This path is, among polynomial confounds, consistent with the estimated event-time path, the least 'wiggly' path with the lowest polynomial order (Rambachan and Roth, 2023). We overlaid the predicted pre-trends in panels (b) and (e); and subtracted them from the estimated treatment effects in panels (c) and (f), following the approach outlined by Dobkin *et al.* (2018) and Freyaldenhoven *et al.* (2021). We focused on the quantity and unit value specification since the value and TEU's specifications show similar pre-trends as the quantity specification.

driver behind the observed trade effects. However, because the linear pre-trend analysis cannot speak to trend growth in the absence of global container shipping disruptions, it could be that the 'event' caused an unrelated trend break in US containerised agricultural exports. Therefore, the actual trade effects are likely between the baseline and pre-trend robust estimates.

Fixed Effects – The baseline model uses port-destination-product fixed effects that we interacted with event year and month time indicators. This fixed-effects specification is demanding as it absorbs a considerable share of variation. To test the robustness of our identification strategy regarding this stringent choice of fixed effects, we re-estimate the baseline model using different combinations of fixed effects. These alternative specifications are in line with the more traditional gravity-type regression design (for example, Grant *et al.*, 2021; Weidner and Zylkin, 2021). However, they also allow for arbitrary correlations that our more stringent fixed effects can capture. We summarise the results of these estimations in Table A.2.[15] The estimated treatment pathways indicate that our results are robust to the fixed-effects choice. There is no evidence for significant pre-trends for the quantity specification, and the post-event treatment effects show a similar pattern and magnitude as the baseline results. In addition, the average post-event treatment effects are statistically indifferent from the baseline at conventional levels of statistical significance. Therefore, the calculated trade effects are robust to different fixed-effects structures.

[15]We report average post-event treatment effects for value, TEUs, quantity, and unit value. Note that we show all potential combinations of fixed effects based on the port-destination-product triples. The parameter estimates can be obtained upon request from the authors.

Trade Data Aggregation – We investigate the impact of different export data aggregations in Table A.3. The analysis is insightful because the statistical analysis at the port-destination-product level excludes singleton observations that show no variation over time. By aggregating the export data at different observation levels based on the port-destination-product triples, we can investigate the robustness of the parameter estimates to the exclusion of such observations (Gründler and Krieger, 2022). Comparing average pre-event and post-event treatment effects, we find strong evidence for the absence of significant pre-trends in the TEUs and quantity specifications. At the same time, we observe that the post-event coefficients stay relatively stable for the value and unit value specification. However, stronger evidence for significant pre-trends emerges the more we aggregate the trade data. These findings show the importance of controlling for product demand and supply factors at the port and destination levels, and a considerable information loss due to data aggregation (Orcutt *et al.*, 1968). For our primary outcome of interest, export quantity, we find strong evidence for stable average post-event treatment effects across aggregation levels. The coefficients are similar at conventional levels of statistical significance for most aggregation levels.

Zero Trade Flows – We compare two alternative estimation approaches to deal with zero trade flows in Figure A.5. Panel (a) shows estimates for a linear regression model and the quantity specification, where we log-transformed the outcome and dropped zero observations. We find evidence of statistically significant average post-event treatment effects for the linear regression. The average trade effect is −5 per cent for the post-event period. At the same time, the dynamic parameter estimates show a similar pattern to the non-linear regression that accurately accounts for zero trade flows. An alternative to retaining zero trade flows is the inverse hyperbolic sine (IHS) transformation that allows us to approximate the natural logarithm (Bellemare and Wichman, 2020; Aihounton and Henningsen, 2021). Panel (b) shows that the estimated treatment coefficients are similar to the baseline results regarding the treatment pathways, but smaller in magnitude for the IHS transformation. We find that the average post-event trade effect is −5 per cent. The estimates show that linear regression without zeros and the IHS transformation cannot address zero trade flows consistently. A further concern is the scale-dependency of the estimated treatment pathways, which is not a problem for the non-linear Poisson PML estimator (Silva and Tenreyro, 2006; Correia *et al.*, 2019).

Pseudo Treatment and Control Group – A potential concern regarding our identification strategy relates to unobserved changes in the post-event period unrelated to the event year. To test for such a confound, we estimate the baseline model for the quantity specification using a placebo treatment design, in which we assigned 2020 as the treatment year. Panel (a) of Figure A.6 lends strong support for our identification strategy as the post-event parameter estimates are jointly insignificant at conventional levels of statistical significance. Next, we compare the impact of using a different control group in panel (b) of Figure A.6. Instead of relying on containerised agricultural exports from 2014 to 2017 as the control group, we now use data for 2016 to 2020 and test how robust our parameter estimates are to that choice. A concern with that control group is the coincidence of the 2018 China–US trade war that could induce spurious regression. Despite these concerns, the estimated post-event treatment pathways support the robustness of our research design. Although the average post-event trade effect is slightly smaller than for the baseline comparison group, the coefficient estimates are in the same ballpark. However, there is some evidence for significant pre-trends resulting from spurious correlations caused by the 2018 China–US trade war.

Event Month Choice – We investigate the robustness of our event study estimates to the choice of using May 2021 as the event month. Although the insignificant pre-trend test and the flat pre-treatment pathways in panel (c) of Figure 1 provide strong support for the treatment month choice, we test March to July 2022 as alternative treatment months in Figure A.7. Because the pre-trend tests are significant for March, June, and July as the event months, we can exclude these months as the appropriate choice of treatment event. In contrast, the pre-trend test for April 2021 is statistically insignificant at conventional levels. Furthermore, the average post-event treatment effect is 2 per cent larger than our baseline estimate, while the estimated trade losses are the same. Because the event study approach allows us to capture the treatment dynamics relative to the event month and the dynamic treatment effects are similar around May 2021, the estimated treatment pathways are robust to the choice of the event month.

Transport Mode and Import Response – We show the treatment pathways for agricultural bulk exports in Figure A.8 and containerised agricultural imports in Figure A.9. In addition to increasing domestic inventory and sales, shipping agricultural products by bulk carriers and substituting imports with domestic production are the main pathways of adjustment to container shipping disruptions.[16] The dynamic treatment estimates in panel (b) of Figure A.8 indicate that shipping disruptions also affected agricultural bulk exports, which were down by about 24 per cent compared to the counterfactual between May 2021 and January 2022. The findings prove limited substitution between transport modes and provide no evidence for positive price effects for agricultural bulk shipments. The event studies for containerised agricultural imports in Figure A.9 indicate adverse trade effects of container shipping disruptions on the agricultural import side. Panel (c) shows similar event pathways for containerised agricultural imports and exports. The average post-event trade effect is about −8 per cent, while there is also some evidence for positive unit value effects. These findings indicate limited substitution by transport mode and provide no compelling evidence for changing import competition at the aggregated level.

4.3 Treatment heterogeneity and mechanisms

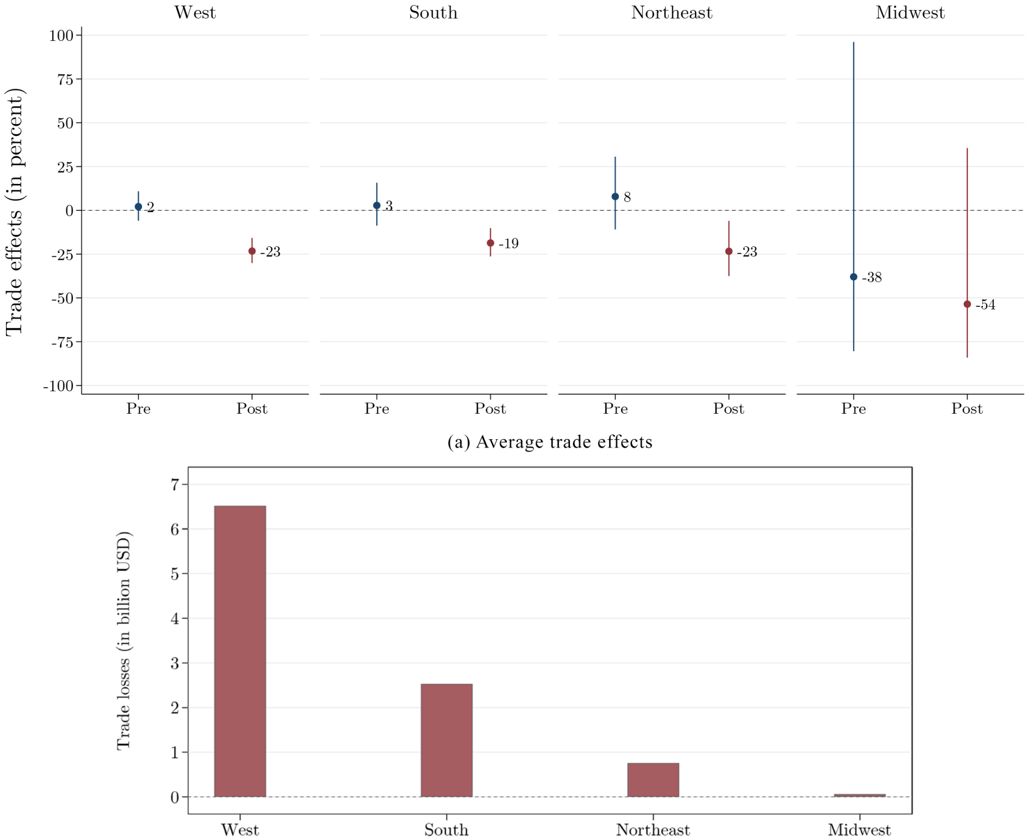
Regional Trade Effects – Figure 3 shows that the average trade effects and overall export losses vary widely across US geographic regions. We classified all US ports according to the census region they belong to (United States Customs and Border Protection, 2020). We adjusted the baseline model by interacting the event-time coefficients with the census regions to estimate the regional trade effects. Panel (a) provides no evidence for significant pre-trends for Western, Southern, and Northeastern ports. At the same time, we find some evidence for ports in the Midwest.[17] The adverse trade effects are the largest for Western and Northeastern port regions. However, these average post-event trade effects are not statistically different from those estimated for Southern ports. Panel (b) in Figure 3 shows that the average trade effects translate into considerable export losses. We assumed constant unit prices for April 2021 (the pre-event month) to estimate the trade losses by US census regions based on the regional dynamic post-event treatment effects. Because we find no significant treatment effects for the unit value specification after controlling for linear pre-trends, the pre-event unit values are a reliable measure of the actual price level. These results suggest containerised agricultural exports from Western and Southern

[16]Another pathway of agricultural export adjustment is air freight. For instance, with air freight rates running from USD 2.50 to USD 5 per kg to China, this transport mode is cost-prohibitive for most agricultural products. A standard container (TEU) can hold about 20,000 kg, implying that air freight would cost 80 to 160 times as much as maritime shipments. Therefore, air freight is an unlikely pathway of adjustment to container shipping disruptions.

[17]The overall reduction in containerised agricultural exports from Midwestern ports on the Great Lakes since 2014 can explain these differences.

Figure 3

Average Post-event Trade Effects and Overall Export Losses by US Census Region



(a) Average trade effects

(b) Trade losses

Note: We follow the approach outlined by de Chaisemartin and D'Haultfœuille (2020) to calculate average post-event treatment effects, and obtained trade effects using the formula $(\exp(\overline{\beta}_k) - 1) \times 100$ based on the quantity specification. Export losses were calculated based on constant unit values for April 2021.

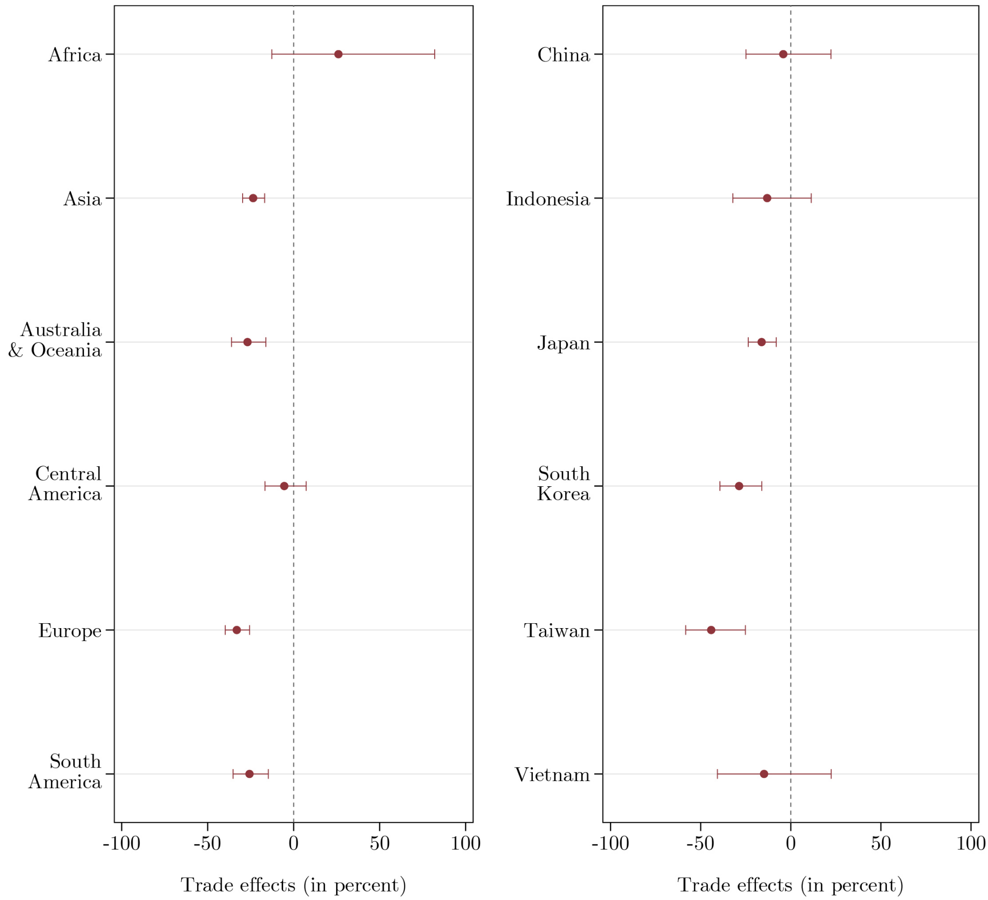
ports contracted by USD 6.5 billion and USD 2.5 billion, respectively. We find that export losses for Northeastern ports are substantially smaller at about USD 0.8 billion, while we find no evidence of economic damages for Midwestern ports.

Export Destinations – We compare average post-event trade effects by export destination in Figure 4.[18] Panel (a) shows that containerised agricultural export volumes from US ports

[18]We further explore heterogeneity according to the economic development stage and income level of the destination countries in Table A.4. Comparing average post-event treatment effects for developed with developing economies in panel (a), we find evidence for considerable treatment differences for the quantity specification at conventional levels of statistical significance. We explore this heterogeneity further in panel (b), comparing those countries according to their income level. We find evidence that high-income countries drive the overall adverse treatment effects. The adverse trade effects for the quantity specification are considerably larger for countries with high rather than middle and low income.

Figure 4

Average Post-event Trade Effects by Continent and Major Asian Export Destination



(a) By Continent (b) Asian export destinations

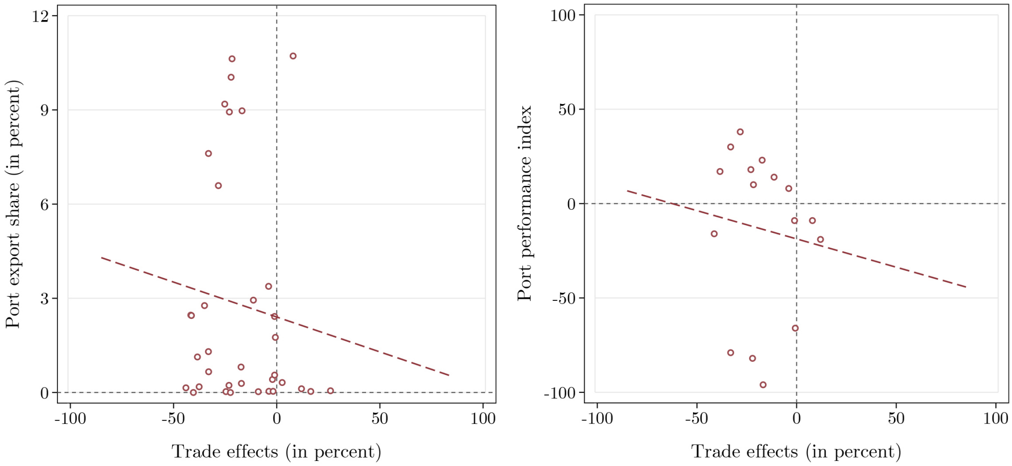
Note: We follow the approach outlined by de Chaisemartin and D'Haultfœuille (2020) to calculate average post-event treatment effects, and obtained trade effects using the formula $(\exp(\overline{\beta}_k) - 1) \times 100$ based on the quantity specification. We excluded North America from panel (a) because most trade with Canada and Mexico occurs via land. We selected the top six Asian export destinations based on the pre-event months in panel (b).

contracted the most on the route to Europe (–33 per cent), Australia and Oceania (–27 per cent), and South America (–26 per cent). Exports to Asia (–24 per cent) and Central America (–5 per cent) fell less, while we find no evidence of adverse trade effects for Africa. However, the estimated trade losses reveal a different picture. By calculating export losses based on constant unit values for April 2021, we find that containerised agricultural exports to Asia contracted by almost

We find no evidence of significant post-event treatment effects for those countries at the lower end of the income distribution. These results show that containerised agricultural exports to richer countries were more affected by global container shipping disruptions.

Figure 5

Average Post-event Trade Effects by Port Size and Port Performance



(a) Port size (b) Port performance

Note: We follow the approach outlined by de Chaisemartin and D'Haultfœuille (2020) to calculate average post-event treatment effects, and obtained trade effects using the formula $(\exp(\overline{\beta}_k)-1)\times 100$ based on the quantity specification. We defined port size as the share of each port in the overall US export value of containerised agricultural products during the pre-event months. Port performance is measured by the administrative port performance index in the 2020 container port performance report (World Bank and IHS Markit, 2022). The overlaid dashed line represents the linear fit.

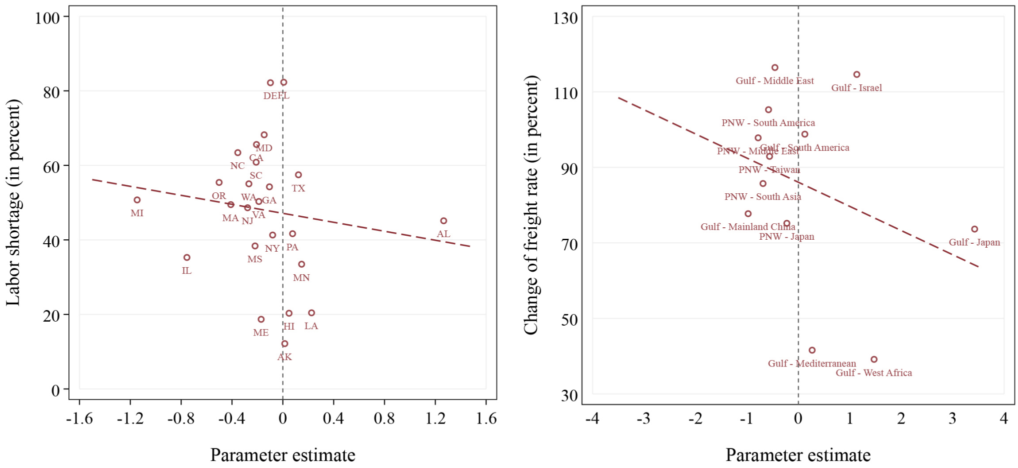
USD 6.9 billion, followed by Europe (USD –2.2 billion) and South America (USD –0.6 billion). The economic losses for other continents are smaller. Panel (b) distinguishes average post-event trade effects by major export destinations in Asia. We selected the top six destinations based on the export value in the pre-treatment month (April 2021). The considerable reduction in containerised agricultural exports to Japan (–16 per cent), South Korea (–29 per cent), and Taiwan (–44 per cent) drive the overall adverse trade effects. We find only limited evidence for export losses to China and Hong Kong.[19] Zooming in on the associated trade losses, we estimate that exports to South Korea contracted the most, dropping by USD 1.4 billion, followed by Japan (USD –1 billion) and Taiwan (USD –0.9 billion). These trade impact estimates provide strong evidence for substantial geographic heterogeneity in the trade effects.

Port Size and Performance – We investigate the association between average post-event trade effects, port size, and port performance in Figure 5. Panel (a) plots the trade effects against the export share. We defined the export share based on a port's share in overall containerised agricultural exports during the pre-event period. The data indicate a distinct pattern. Eight ports are responsible for 73 per cent of all containerised agricultural exports. Apart from Houston, TX, all critical

[19]Figure A.10 shows event study estimates for containerised agricultural exports to China and all other countries. The large confidence intervals in panel (a) indicate considerable product heterogeneity for containerised agricultural exports to China. However, there is limited statistical evidence for significant treatment effects since all dynamic treatment estimates are statistically indifferent from zero. These findings imply the identification strategy can accurately account for destination-product-specific trade shocks, such as the Phase One deal between the USA and China implemented in February 2020, through the event year and month port-destination-product fixed effects.

Figure 6

Average Post-event Trade Effects, Local Labour Shortages, and Freight Rates



(a) Local labour shortage (b) Freight rates

Note: We follow the approach outlined by de Chaisemartin and D'Haultfœuille (2020) to calculate average post-event treatment effects, and obtained trade effects using the formula $(\exp(\overline{\beta}_k) - 1) \times 100$ based on the quantity specification. The magnitude of the local labour shortage is calculated using state-level transportation and warehousing industry employment data from the Bureau of Economic Analysis (2024), measuring the ratio of excess employment in 2021 relative to average employment levels between 2003 and 2020. Freight rates were obtained from Bloomberg (2024), and the change in freight rates is calculated by comparing the average freight rate during the post-period (May 2021 to January 2022) with the average level for the corresponding months (May to January) in the pre-event years (2017 to 2020) at the port level. The overlaid dashed line represents the linear fit.

ports experienced export losses between 17 and 33 per cent. In contrast, the trade effects for non-major ports vary more widely between –44 and 26 per cent. These results indicate that agricultural exporters redirected containerised exports to other ports that considerably expanded their containerised agricultural shipments. For instance, Port Hueneme, CA, expanded its agricultural exports by 12 per cent, while Houston, TX, and Panama City, FL, grew their agricultural exports by 8 per cent and 26 per cent, respectively. Overall, we find evidence for a negative relationship between the port export share and the trade effects. Panel (b) plots the average post-event trade effects against the administrative port performance index published by the World Bank and IHS Markit (2022).[20] We find limited evidence of a statistically significant relationship between the port performance index and the average post-event trade effects. Again, we see two groups ranked above and below the zero line for the port performance index. In addition, the average post-event trade effects for both groups are indistinguishable from one another at conventional levels of statistical significance. These results show that the relative performance within the group of US ports, for which reliable information on port performance is available, does not explain the trade losses.

Local Labour Shortages – Panel (a) of Figure 6 shows the relationship between labour shortages across various US states in the transportation and warehousing industry, and the average

[20]Note that the World Bank's ranking includes 16 out of 104 US ports in our data set. These ports tend to be larger than the average US port shipping agricultural products to foreign markets.

post-treatment effects at the port level. The estimates indicate that states experiencing more severe labour shortages experienced larger container shipping disruptions. States on the West Coast, such as Washington, Oregon, and California, experienced considerable labour shortages, and saw container shipping falling by −26.7 per cent, −50.1 per cent, and −20.7 per cent on average. In contrast, states like Louisiana, Alaska, Minnesota, and Maine experienced minimal trade effects while facing fewer labour force disruptions. These estimates indicate that labour shortages were a key mechanism contributing to logistical challenges at US ports in 2021.

Freight Rates – Panel (b) of Figure 6 shows the relationship between changes in freight rates before and after the disruption, and the average post-treatment effects. The figure includes major trading routes between the USA and other countries or regions. It shows that, compared to the pre-event period, freight rates in the post-event period soared significantly, with increases ranging from 30 to 120 per cent for routes originating from Gulf ports. In comparison, freight rates from the Pacific Northwest (PNW) remained high (between 70 and 110 per cent). In contrast to the Gulf ports, most routes originating from the PNW saw negative average post-treatment effects. Meanwhile, routes from the Gulf to locations such as West Africa and the Mediterranean experienced relatively modest freight rate changes and, correspondingly, only limited trade losses. As indicated by the linear fit, the analysis reveals that routes with higher increases in freight rates generally experienced larger post-event trade effects. These estimates align with the findings by Hossen *et al.* (2024), suggesting that the significant increase in freight costs contributed to the trade disruptions in 2021.

4.4 Product heterogeneity

Trade Effects by HS Chapter – We show the average post-event trade effects in relative terms and the associated trade effects in USD in Figure A.11. The estimated trade effects at the HS chapter level provide evidence for consistent and considerable adverse consequences of global container shipping disruptions across product groups. As shown in panel (a), in relative terms, tobacco products (chapter 24, −52 per cent) experienced the most considerable adverse trade effects, followed by cereals (chapter 10, −47 per cent) and vegetable plaiting materials (chapter 14, −39 per cent). In contrast, we find evidence of positive trade effects for sugars and sugary preparations (chapter 17, 6 per cent), and meat preparations (chapter 16, 3 per cent). Panel (b) shows that the percentage trade effects do not translate into equally large trade losses. We find that meat (chapter 2, USD −1.9 billion), edible fruit and nuts (chapter 8, USD −1.2 billion), and oilseeds (chapter 12, USD −0.9 billion) experienced the sharpest drops in containerised agricultural exports between May 2021 and January 2022. Prepared animal feed (chapter 23) and beverages (chapter 22) closely follow, recording export losses of USD 0.8 billion and USD 0.6 billion, respectively. In addition, the observed trade gains for some products are negligible and sum to less than USD 40 million compared to the counterfactual. Since these estimates are also insignificant at conventional levels of statistical significance, we conclude that global container shipping disruptions did not benefit trade in any particular product group while causing adverse but heterogeneous trade effects across commodity groups.[21]

[21]Table A.5 shows post-event treatment effects and trade losses by HS section for major US ports. The estimates indicate that adverse trade effects of container shipping disruptions operated mainly through California ports and agricultural products listed under HS sections 1, 2, and 4.

Average Trade Effects by Product Classification – We compare the average post-event trade effects for four product classifications in Figure A.12. We interacted the dynamic treatment coefficients with the product classification of agricultural products by Regmi *et al.* (2005) in panel (a). We combined processed and semi-processed products into one category. There is no evidence for significant pre-trends for each interaction term. The adverse trade effects are largest for the bulk category (−37 per cent). Processed products and horticulture/produce experienced a trade decline of about −20 per cent. The Bulk, Intermediate & Consumer Oriented (BICO) classification of agricultural products, developed by the Foreign Agricultural Service (2022), reveals similar patterns in panel (b). Bulk products experienced the most considerable adverse trade effects, while these effects are more minor for intermediate (−21 per cent) and consumer-oriented products (−16 per cent). Next, we used the classification by Rauch (1999) to distinguish between homogenous and differentiated products in panel (c). The results indicate larger adverse trade effects for homogenous (−29 per cent) than differentiated products (−13 per cent). These results indicate that the trade adjustment costs are higher for homogenous than differentiated products. Finally, we classify all products according to the price level in the pre-event months into low, medium, and high unit values in panel (d). The results indicate more considerable trade effects for products with a low unit value. The average trade effect for products with a high unit value is half that observed for products with a low unit value. This product heterogeneity indicates that exporters substituted containerised agricultural exports with a low unit value with products of higher unit value. This pattern can be explained by greater profit margins for high-value products, which make exporters prioritise exporting such products (Fernandes and Winters, 2021; Jiao *et al.*, 2022).

5.0 Conclusions

This paper used a non-linear panel event study with high-dimensional fixed effects to assess the dynamic treatment effects of the 2021 global container shipping disruptions on US containerised agricultural exports. Our empirical strategy identified the trade effects through variation in trade flows from previous years at the port-destination-product level, allowing us to handle seasonality and other arbitrary correlations, and measure the average post-event treatment effects. The baseline results show that US containerised agricultural exports were 22 per cent below the counterfactual from May 2021 to January 2022. The adverse trade effects translate into USD 10 billion in export losses for all US ports. Western and Southern US ports were the most affected, experiencing aggregated export losses of USD 6.5 billion and USD 2.5 billion, respectively. The product heterogeneity analysis shows considerable export losses for meat, edible fruits and nuts, oilseeds, and animal feed. The estimated trade losses for some commodities exceed those of the 2018 China–US trade war (Carter and Steinbach, 2020). In addition to raising inventory costs, the excess supply exerts pressure on domestic prices, likely benefiting domestic consumers and some input users (Martin and Anderson, 2012; Autor *et al.*, 2021).

The paper expands on earlier work concerned with the adverse trade effects of the coronavirus pandemic (for example, Arita *et al.*, 2021; Verschuur *et al.*, 2021a, 2021b; Arita *et al.*, 2022). These studies showed that global agricultural trade decreased by 7 to 9 per cent in 2020 compared to the counterfactual, revealing considerable heterogeneity across countries and product groups. However, few studies are concerned with the impact of global container shipping disruptions on agricultural trade. Our research expands on the initial California-specific impact assessment by Carter *et al.* (2023), the qualitative analysis by Kent and Haralambides (2022), the US-wide assessment of aggregated trade effects by Steinbach (2022), and the analysis of a potential mechanism by Hossen *et al.* (2024). We contribute to this literature by measuring the trade effects of global container shipping disruptions at the product level, providing evidence of considerable heterogeneity across geographic regions and product groups, and assessing potential mechanisms underlying the treatment heterogeneity. A caveat of our research design is that we cannot observe internal trade flows for treated and untreated units. Such trade flows are essential to understanding the domestic margin of adjustment to trade policy shocks (for example, Anderson and Van Wincoop, 2003; Heid *et al.*, 2021; Yotov, 2022). This limitation implies that our research design cannot speak to the welfare implications of global container shipping disruptions. Because agricultural supply tends to be inelastic in the short run (that is, commodities affected by container shipping disruptions can be stored for some time or consumed domestically), the welfare impact could be smaller than the pure trade effects (Roberts and Schlenker, 2013; Boehm *et al.*, 2020). In addition, for the marketing year 2021/22, the ending inventories for some export-oriented commodities – such as almonds and walnuts, are at an all-time high, more than twice as large as in the previous marketing year, causing additional welfare losses by putting pressure on domestic prices and causing high storage costs (Carter and Steinbach, 2022).

We also contribute to the growing literature concerned with the dynamic response of international markets to trade shocks. By combining high-frequency trade data, an event study design, and high-dimensional fixed-effects models, we utilise a novel method to measure the dynamic impact of trade shocks with limited information on differences in the treatment intensity across cross-sectional units. Inspired by Grant *et al.* (2021) and Arita *et al.* (2022), we exploit variation in untreated temporal units to construct a counterfactual with similar pre-trends and seasonality patterns in the post-event period. Combining their approach with an event study design for gravity-type regression models is a promising avenue for future research lacking a reliable control group from the same period, to use as counterfactual or construct synthetic control units (Abadie *et al.*, 2010; Abadie, 2021; Arkhangelsky *et al.*, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2022). We provide strong empirical evidence that variation from previous untreated periods within the same port-destination-product triples can be a reliable control group. Such insights are particularly beneficial for the international trade literature, focusing on the response to trade shocks. These shocks are often characterised by considerable treatment dynamics over time (for example, Amiti *et al.*, 2021; Malgouyres *et al.*, 2021; Ahn and Steinbach, 2022; Ding *et al.*, 2022; Steinbach, 2022). Ignoring such temporal heterogeneity and potential pre-trends can miss the 'true' trade effects of trade shocks (Attinasi *et al.*, 2022). These insights could be beneficial for future empirical studies concerned with trade policy shocks, such as research on the trade effects of regional and multilateral trade integration, and preferential trade provisions (for example, Grant and Lambert, 2008; Grant and Boys, 2012; Breinlich *et al.*, 2021; Arita *et al.*, 2022; Curzi and Huysmans, 2022; He, 2022).

The paper highlights the considerable consequences of inadequate port infrastructure, port congestion, and container shortage for US agriculture by systematically evaluating the trade effects of the 2021 container shipping disruptions. Although federal and state governments have implemented several measures to combat shipping delays, and improve access to shipping containers, these measures will likely take time. The federal government invested USD 14 billion in US ports and waterways in the fiscal year 2022 alone (White House, 2022). This investment is part of the Bipartisan Infrastructure Investment and Jobs Act, including USD 5 billion targeted at port infrastructure – explicitly, the American Association of Port Authorities (2022). For example, these funds will help to improve commercial navigation, and allow larger and more ships to pass through the Port of Long Beach. In addition, California's administration proposed to invest USD 1.4 billion in supply chain resilience and port infrastructure in the 2022–3 state budget (California State Legislature, 2022). Although these investments could help alleviate the port congestion problems experienced at California ports, these port and hinterland infrastructure upgrades will take time. Federal and state governments also implemented several short-term measures to provide further relief. For instance, the US Department of Agriculture established several partnerships to ease port congestion and restore disrupted shipping services to agricultural commodities in January 2022 (United States Department of Agriculture, 2022). The partnership with the Port of Oakland provided a 25-acre 'pop-up' site that offers space to prepare empty containers. The programme used Commodity Credit Corporation funds to cover 60 per cent of the start-up costs and offered additional support for movement logistics at USD 125 per TEU. Future research may evaluate how state and federal programmes impacted shipments of agricultural products from US ports. Such insights will help advance the resilience of the maritime industry and make agricultural trade more robust to future maritime disruptions.

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