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Working Paper

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April 2022
IATRC
Working Paper #22-01

International Agricultural
Trade Research Consortium

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April 2022
ISSN 1098-9210
IATRC
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Abstract

Containerized exports are significant for U.S. agriculture, especially for certain products, such as meat, tree nuts, and oilseeds. We assess the trade losses to U.S. agriculture arising from shipping container disruptions in 2021. We rely on a non-linear panel event study design to measure the dynamic treatment effects using both bills of lading and Census Bureau export data at the U.S. port level. Our findings are that the volume of U.S. containerized agricultural exports was 22 percent below the counterfactual level from May 2021 to January 2022, amounting to USD 10 billion in export losses. There were differences in the trade effects across geographic regions and product groups. We find that Western and Southern ports faced the brunt of export losses, with meat, edible fruits and nuts, oilseeds, and animal feed being the most affected.

Keywords: Shipping container disruptions, containerized trade, U.S. agricultural exports, dynamic treatment effects

JEL codes: F14; Q17; Q18

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1. Introduction

The coronavirus pandemic had significant 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 United States 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 was 7 to 9 percent below the counterfactual level in 2020. As a result of increased unemployment benefits, stimulus payments, and deferred consumption expenditures, the U.S. personal saving rate increased considerably in the second half of 2020, reaching 27 percent 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 significant expansion of imported goods in containers (Parker et al., 2022). U.S. ports, especially on the West Coast, could not keep up with the additional containerized imports. Over 100 loaded vessels were stranded off the Southern California coast in November 2021. The struggling California ports confirm the results of a World Bank report, which put California near the bottom in terms of port efficiency in 2020 (World Bank and IHS Markit, 2022). Out of 351 ports worldwide, Long Beach was ranked 342, closely followed by Los Angeles (337) and Oakland (334), placing them far behind all other U.S. container ports and behind many ports in developing countries.

Shipping container turnaround time at U.S. ports increased considerably due to port congestion in 2021. For instance, California ports took almost twice as long to handle incoming cargo than in the previous year (Carter et al., 2021). These disruptions meant that empty containers became more valuable in Asia, so freight companies chose to send back more empty containers instead of filling them with agricultural products. As a result, 66 percent of all containers exported from U.S. ports were empty in January 2022. This share increased considerably from a mere 46 percent in 2019. Simultaneously, container freight rates from

Asia to the United States increased sixfold, while those on the backhaul route to Asia almost tripled (Bloomberg, 2022). This difference reflected a considerable increase in the freight rate gap between eastbound and westbound shipments across the Pacific. Similar freight rate increases were observed for other U.S. ports. As a result, U.S. agricultural exporters faced increasing difficulties accessing empty containers and shipping agricultural products abroad, resulting in increased inventories of many agricultural goods.

This paper measures the impact of global shipping container disruptions on U.S. containerized 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 (triple) level. Since exports of other countries or different product categories could also be affected by global shipping container disruptions, we cannot rely on such a comparison group to construct a reliable counterfactual for causal inference. Therefore, as the control group, we employed the U.S. containerized agricultural exports at the port-destination-product level from 2014 to 2017. This choice allows us to measure the causal treatment effects based on a comparison group with similar pre-trends and within-year variation at the port-destination-product level. We center the event study around May 2021 because global shipping container disruptions became a significant issue in 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 U.S. containerized agricultural exports was 22 percent below the counterfactual from May 2021 to January 2022. This translates into a loss of 740,000 twenty-foot container equivalent units (TEUs) exported. These adverse trade effects peaked in November 2021, when U.S. containerized agricultural exports fell short by 130,000 TEUs, resulting in 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. U.S. ports in the West and South were the most adversely affected and experienced aggregated export losses of USD 6.5 billion and USD 2.5 billion, respectively. We find that U.S. exports to Asian countries decreased the most. Our analysis reveals significant export losses for meat, edible fruits and nuts, oilseeds, and animal feed. For some products, the trade losses from global shipping container disruptions were far more extensive than those experienced during the 2018 China - U.S. trade war.

The paper provides three distinct contributions to the growing literature on the trade effects of the coronavirus pandemic and global shipping container disruptions. First, we are the first to quantify the adverse trade effects of global shipping container disruptions on U.S. containerized agricultural exports. Previous ex-post studies on the trade effects of the coronavirus pandemic are limited to 2020 (e.g., Arita et al., 2021; Verschuur et al., 2021a,b; Arita et al., 2022). These studies provide evidence for adverse trade effects in the vicinity of 7 to 9 percent 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 line of the results presented in this paper. Carter et al. (2021) provide an initial quantitative assessment of the trade effects caused by global shipping container disruptions for California ports, showing evidence of trade destruction of about USD 2.1 billion from May to September 2021. These estimates are in line with the qualitative work by Kent and Haralambides (2022), the U.S.-wide assessment of the aggregated trade effects of container trade disruptions by Steinbach (2022), and our estimated heterogenous trade response across U.S. port regions and product groups.

Second, this paper speaks to the growing literature concerned with the dynamic response of international trade flows to trade policy shocks by using high-frequency trade data, event

study methods, and high-dimensional fixed effects 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 (e.g., 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 characterized by many treatment dynamics over time (e.g., 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 shipping container 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 (e.g., Grant and Lambert, 2008; Grant and Boys, 2012; Breinlich et al., 2021; Arita et al., 2022; Curzi and Huysmans, 2022; He, 2022).

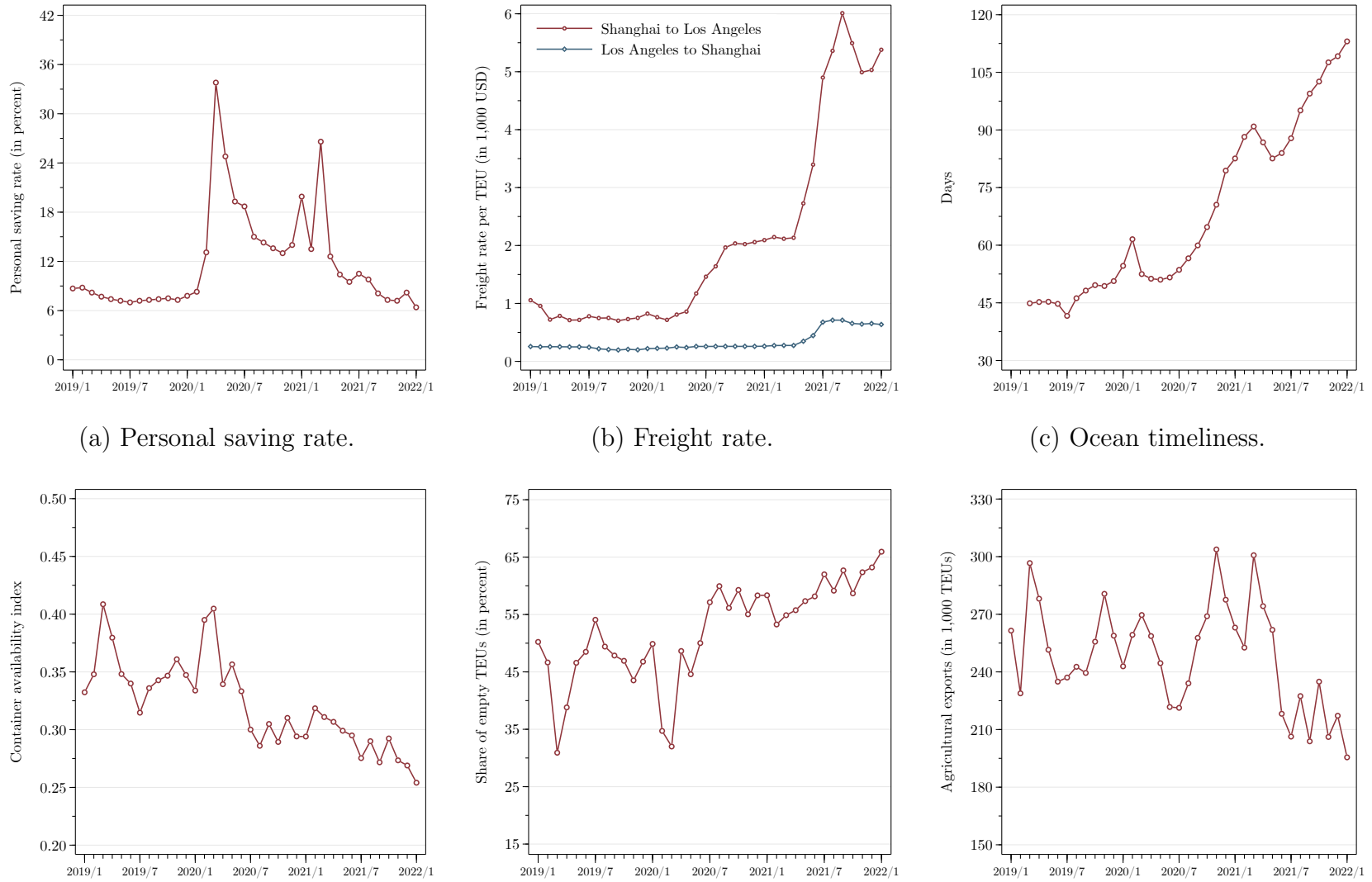
Third, we contribute to the empirical literature measuring the impact of trade policy shocks with limited information on differences in the treatment intensity across cross-sectional units. Since there is little previous work on how susceptible trade flows are to global container shipping disruptions, 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. These units show similar underlying variation in within-year trade flows and serve as a counterfactual defined at the port-destination-product level. The fixed effects allow us to

control for unobserved changes in the demand and supply patterns specific to 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, enabling researchers to measure the causal treatment effects of global shipping container disruptions when combined with high-dimensional fixed effects (Freyaldenhoven et al., 2021). Our empirical work is in line with Grant et al. (2021) and Arita et al. (2022), who used a similar but static research design to evaluate the trade effects of the 2018 China-U.S. trade war and the coronavirus pandemic.

2. Background

A multitude of demand, supply, and transport cost factors contributed to global shipping container disruptions.[1] Figure 1 shows trends in the five primary drivers. First, increased unemployment benefits, stimulus checks, and deferred consumption expenditures grew the U.S. personal saving rate considerably in 2020 (Carroll et al., 2020; Coibion et al., 2020). As shown in (a), the personal saving rate peaked in April 2020 at 34 percent. It remained at an average of 14 percent until September 2021, when the rate returned to the pre-pandemic level. In response to the fading pandemic, households released more than USD 2.3 trillion in excess savings from Spring 2021 onward (O'Trakoun, 2021). Growing earnings in most sectors exerted additional pressure on international supply chains (Bell et al., 2021; Domash and Summers, 2022). The increasing demand for durable goods contributed to more than 14 percent import growth in 2021 compared to the previous year. The majority of these additional imports arrive via container ships in the United States (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.

[1] Although additional factors likely contributed to U.S. container trade disruptions, we focus on the five primary factors that caused the observed trade patterns. Some of them are strongly correlated. Hence, we abstain from attributing the trade effects to a particular factor as the sole explanatory throughout the paper. This issue remains open for future research concerned with global shipping container disruptions.



(a) Personal saving rate.

(b) Freight rate.

(c) Ocean timeliness.

(d) Container availability index.

(e) Empty shipped TEUs.

(f) Containerized agricultural exports.

Figure 1: Stylized facts.

Note. We show the seasonally adjusted annual personal saving rate from the Federal Reserver Bank of St. Louis (2022) in panel (a), the transpacific Drewry container index from Bloomberg (2022) in panel (b), and the ocean timeliness index on the transpacific eastbound route from Flexport (2022) in panel (c). We used PIERS data from IHS Markit (2022) to construct figures for panels (d) to (f). We constructed the container availability index in panel (d) following the approach outlined by XChange (2022). The index is smaller than 0.5 if more containers enter U.S. ports than leave. We relied on the approach by Carter et al. (2021) to calculate the share of empty containers leaving U.S. ports in panel (e) and defined containerized agricultural exports by HS chapters 0 to 24 in panel (f).

Second, the growing demand for durable goods from Asia and the slowed turnaround times resulted in a substantial increase in maritime freight rates, as (b) shows. Container freight rates from Asia to the United States increased sixfold, remaining at more than USD 5,000 per TEU into January 2022 (Bloomberg, 2022). At the same time, freight rates on the backhaul route to Asia increased to about USD 600 per TEU starting from May 2021, almost tripling compared to the previous year. 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 (c). Fourth, the number of available containers diminished considerably, as shown by the container availability index in (d). The index measures the movement of full containers through U.S. ports. A value of 0.5 means that the same number of containers leave and enter the United States in a given 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 containerized 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 U.S. ports, as (e) shows. Many shippers decided to cancel contracts and refused to supply empty containers to U.S. exporters, returning them unfilled to Asia instead. As a result, the share of empty containers doubled from May 2021, reaching an all-time high of 66 percent in January 2022. This share was considerably higher for California ports, with almost 80 percent of exported containers shipped out empty in November 2021.

The observed interplay of port productivity, demand, supply, and transport cost factors contributed to global shipping container disruptions and meant that containerized agricultural exports fell significantly in 2021. Aggregate trade data show that 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 (f) of Figure 1. These adverse trade effects vary considerably across geographic regions and between product groups, pointing toward considerable heterogeneity in the trade response to global shipping container disruptions.

3. Methods and Data

3.1 Empirical Approach

We rely on a panel event study approach to assess the dynamic treatment effects of global shipping container disruptions on containerized agricultural exports from U.S. ports. The baseline model 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. 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, and the month with t. We define the outcome variable with y_{ijst} and study four primary outcomes, namely the free on board (FOB) export value (in USD), TEUs, quantity (measured either as count or in kilograms), and unit value (defined as the value divided by the quantity). 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 could confound the relationship of primary interest. They are flexible over time because multiple factors that likely vary within and across years determine product demand, supply, and trade costs. Note that the combination of port-destination-product and time fixed effects resembles the traditional two-way fixed effects (TWFE) model (Jochmans,

2017; de Chaisemartin and D'Haultfoeuille, 2022). 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. For instance, most agricultural commodities face seasonality patterns in export volumes. Moreover, the port-product-time fixed effects also account for other time-variant factors that are predictive of the outcome and correlated with the treatment. For instance, such characteristics are port infrastructure, freight rates, and anchor time (Clark et al., 2004; Korinek and Sourdin, 2010; Jacks and Pendakur, 2010; de Soyres et al., 2020). The term $\sum_{k=-8}^{8} \beta_k r_{ijs,t-k}$ measures the dynamic treatment effects of global shipping container disruptions on containerized agricultural exports from U.S. ports. The baseline regression model is flexible to some degree, i.e., it allows the treatment effect to be dynamic before and after the first reported supply chain issues. We center the event study around May 2021 because port congestion and container shortages became a major bottleneck in May 2021. This choice is informed by the observed changes in demand, supply, and transport cost factors, as described in Section 2.

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-month and port-destination-product-year levels and thus captured by $\alpha_{ijs,mo}$ and $\alpha_{ijs,yr}$. To include these fixed effects and identify the treatment effects of global shipping container disruptions, we require a control group that shows the same trends in the pre-treatment period and is not affected by global shipping container disruptions. Since we cannot rely on trade data from other countries or other product categories to construct a reliable counterfactual at the port-destination-product level, we resort to U.S. containerized 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 compari-

son group with similar pre-trends at the port-destination-product level.[2] Our identification strategy draws on Grant et al. (2021) and Arita et al. (2022), who used a similar research design and a static regression approach to evaluate the trade effects of the 2018 China-U.S. trade war and the coronavirus pandemic. Lastly, we denote the multiplicative error term with ϵ_{ijst}.

The outcome variable y_{ijst} represents the non-negative integer count of containerized 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 the outcome is a count. A linear regression model is incapable of identifying 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, it would be impossible to obtain unbiased estimates of the relationship. Therefore, we directly model the relationship of interest between containerized agricultural exports and the treatment variables to account for this issue. 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

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

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. An additional advantage is that the estimator allows us to deal with zero trade flows consistently (Silva and Tenreyro, 2006). We follow standard practice and rely on a linear regression model for the unit value specification applying a log transformation of the outcome. We account for the high-dimensional fixed effects by using a modified version of the iteratively re-weighted least-squares (IRLS) 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).[3]

3.2 Data

We sourced export data for all U.S. ports from the United States Census Bureau (2022). Their port-level trade dataset provides monthly export statistics for all U.S. ports and export destinations. In addition to the export value and shipping volume, the dataset includes information on the transport mode (air, bulk vessels, and containerized vessels). We aggregated the trade data at the HS subheading (six-digit) level for September 2014 to January 2022. We supplemented this dataset with bills of lading for all U.S. ports from the Port Import/Export Reporting Service (PIERS) (IHS Markit, 2022). PIERS covers all waterborne cargo vessels that enter and exit U.S. ports. This data is sourced directly from the U.S. Customs and Border Protection, averaging about 75,000 reported transactions per day. We used the transaction-level data to construct a detailed account of containerized agricultural

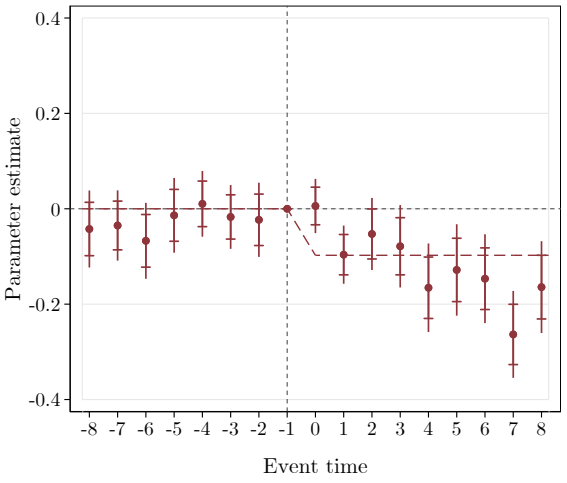
[3] A potential concern is that the high-dimensional fixed effects could create asymptotic estimation bias due to the incidental parameter problem. We applied the correction method proposed by Weidner and Zylkin (2021) to account for this issue. This robustness check provides no support for such estimation 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.

exports measured in TEUs at the monthly level for all U.S. ports at the HS subheading level (Flaaen 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), we find that the final balanced panel dataset covers the monthly value, TEUs, and quantity shipped out of 104 U.S. ports handling containerized agricultural products destined to 222 export destinations and listed under 1,013 HS subheadings from September 2014 to January 2022. We use this dataset to construct the event study panel.

4. Results and Discussion

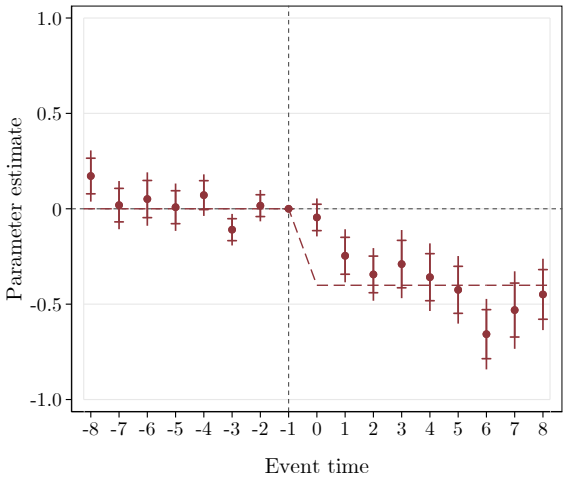
4.1 Baseline

We present the baseline event study estimates for containerized agricultural exports from U.S. ports in Figure 2. 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 percent 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 2 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 behavior. We find no evidence of significant pre-trends for the value, TEUs, and quantity specifications. 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 leveling off treatment effects at conventional levels of statistical significance for all outcomes.



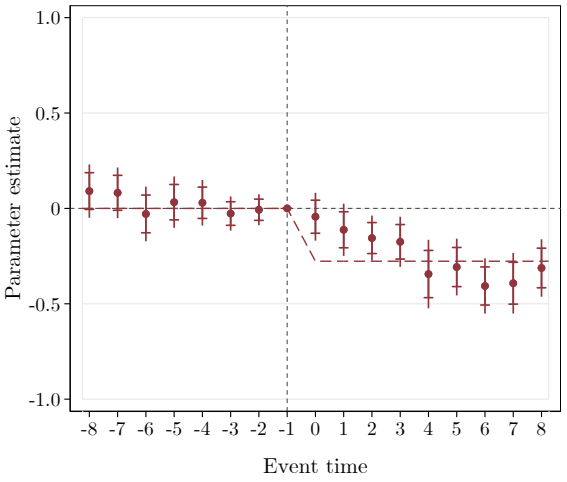
Pre-trends p-value: 0.154 -- Leveling off p-value: 0.001 -- Static effect p-value: 0.125
Pseudo R-squared: 0.921 -- Observations: 1,934,930

(a) Value.



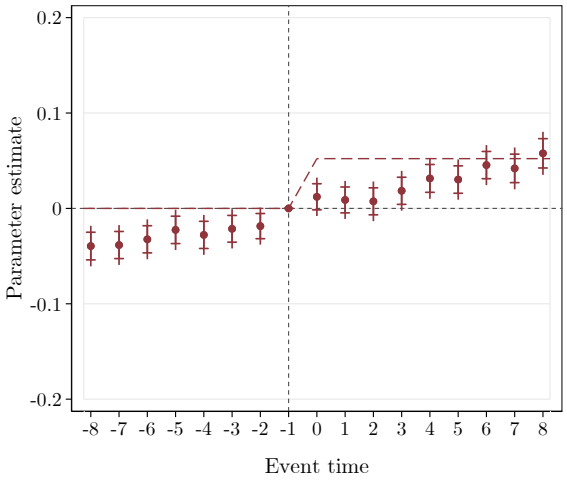
Pre-trends p-value: 0.269 -- Leveling off p-value: 0.144 -- Static effect p-value: 0.067
Pseudo R-squared: 0.896 -- Observations: 1,344,389

(b) TEUs.



Pre-trends p-value: 0.460 -- Leveling off p-value: 0.043 -- Static effect p-value: 0.077
Pseudo R-squared: 0.931 -- Observations: 1,934,930

(c) Quantity.



Pre-trends p-value: 0.000 -- Leveling off p-value: 0.040 -- Static effect p-value: 0.039
Adjusted R-squared: 0.844 -- Observations: 705,092

(d) Unit value.

Figure 2: Event studies for U.S. containerized agricultural exports.

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 percent 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 pretrends, leveling 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. Trade effects are obtained using the formula $(\exp(\beta_k) - 1) * 100$ (Silva and Tenreyro, 2006).

The value specification in panel (a) of Figure 2 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 Fall 2021 and Winter 2021/22. The TEUs specification in panel (b) draws a similar robust picture of adverse treatment effects for containerized agricultural exports. The average post-event treatment effect is -0.373 log points, considerably larger than that for the value specification, pointing toward positive price effects during that period. The event coefficients indicate the most significant adverse treatment effects for event month 6 (November 2021). Since then, some trade recovery has been observable for the TEUs specification. However, containerized agricultural exports remain 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, containerized 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 toward a continued disruption of containerized agricultural exports. In contrast, we find some evidence for 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.

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 containerized agricultural exports and the associated foreign trade losses.[4] We show changes over time in Appendix Figure A.1. On average, monthly containerized agricultural exports were 83,000 TEUs below the counterfactual. These adverse trade effects cumulated in November 2021, when U.S. containerized agricultural exports fell 132,000 TEUs short. Overall, U.S. con-

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

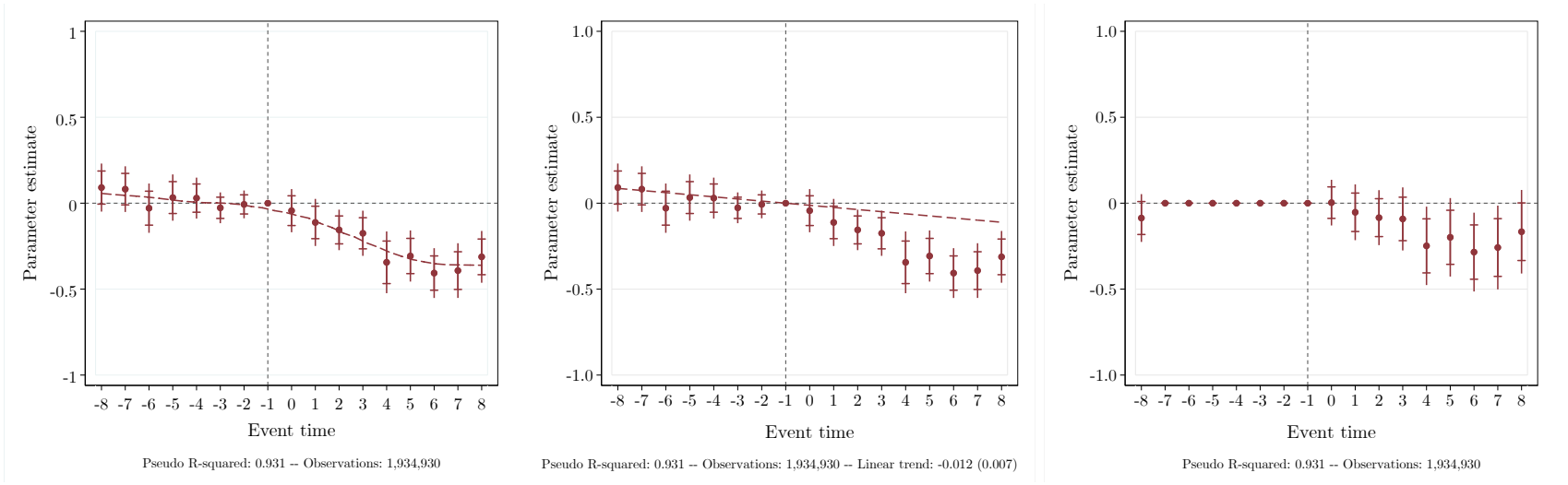
tainerized agricultural exports were 743,000 TEUs below the counterfactual from May 2021 to January 2022. The trade reduction resulted in export losses of about USD 10 billion, representing roughly 22 percent of the overall containerized agricultural exports.[5]

4.2 Robustness

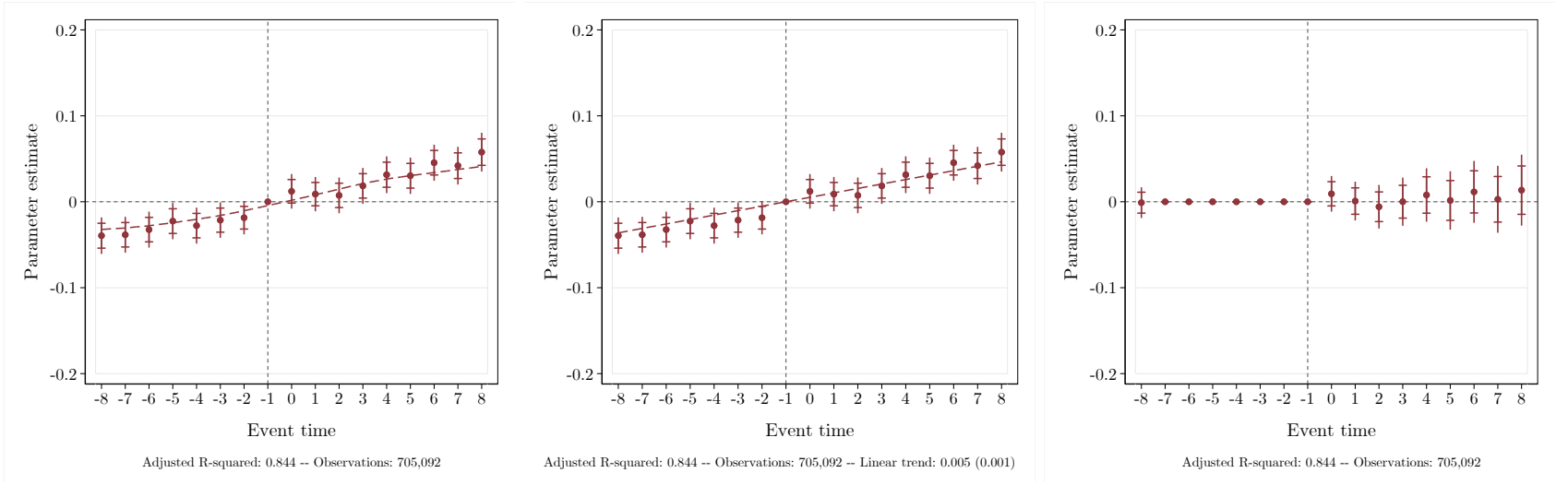
Devil's Advocate Model — A failure to reject the null hypothesis of no pre-event trends does not imply that there is no confounding variable that could threaten the identification of the 'true' treatment effects (Roth, 2021). To test for the presence of a confounding variable, we estimated a devil's advocate model, which assumes that the 'true' value of the treatment effect is zero. We identified the least "wiggly" event-time path, which is, among polynomial confounds consistent with the estimated event-time path, the least "wiggly" path with the lowest polynomial order (Rambachan and Roth, 2021). Panels (a) and (d) of Figure 3 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 shipping container disruptions did causally affect U.S. containerized 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 to be 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

[5] 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 were able to sell some goods in the domestic market or store them.



(a) Quantity, devil's advocate model. (b) Quantity, extrapolated trend. (c) Quantity, subtracted trend.



(d) Unit value, devil's advocate model. (e) Unit value, extrapolated trend. (f) Unit value, subtracted trend.

Figure 3: Devil's advocate model and subtracted potential confound from pre-event periods.

Note. The overlaid dashed line in (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, 2021). We overlaid the predicted pre-trends in (b) and (e) and subtracted them from the estimated treatment effects in (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 TEUs specifications show similar pre-trends as the quantity specification.

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 during the post-event period. This specification identifies the adjusted treatment effects as the deviation between the estimated treatment effect after the treatment and the extrapolated pre-trend.

Figure 3 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 specification decrease from -22.1 percent to -12.6 percent. 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 percent to 0.3 percent, 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 driver behind the observed trade effects. However, because the linear pre-trend

analysis cannot speak to trend growth in the absence of global shipping container disruptions, it could be that the "event" caused an unrelated trend break in U.S. containerized 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 indicators. This fixed effects specification is demanding as it absorbs a significant share of variation. To test the robustness of our identification strategy regarding this more stringent choice of fixed effects, we reestimate the baseline model using different combinations of fixed effects. These alternative specifications are in line with the more traditional gravity-type regression design (e.g., Grant et al., 2021; Weidner and Zylkin, 2021). However, they also allow for arbitrary correlations that our more stringent fixed effects can capture. We summarize the results of these estimations in Appendix Table A.1.[6] 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 effect structures.

Trade Data Aggregation — We investigate the impact of different export data aggregations in Appendix Table A.2. The analysis is insightful because the statistical analysis at the port-destination-product level excludes singleton observations that show no variation over time. To understand better the impact of excluding such observations, we aggregated the trade data at different levels and investigated the stability of the parameter estimates. Comparing average pre-event and post-event treatment effects, we find strong evidence for the absence

[6] We report average post-event treatment effects for value, TEUs, quantity, and unit value. The parameter estimates can be obtained upon request from the authors.

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. 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 not different from one another at conventional levels of statistical significance for most aggregation levels.

Zero Trade Flows — We compare two alternative approaches to deal with zero trade flows in Appendix Figure A.2. 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 significant average post-event treatment effects for the linear regression. The average trade effect is -5 percent 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 terms of magnitude. We find that the average post-event trade effect is -5 percent. 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 no problem for the non-linear Poisson PML estimator (Silva and Tenreyro, 2006; Correia et al., 2019).

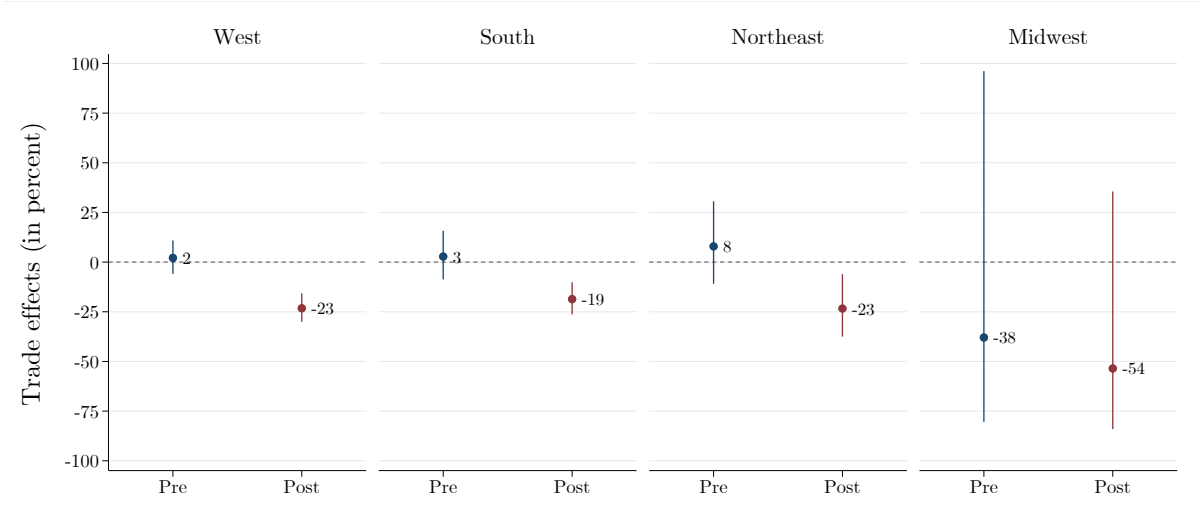
Pseudo Treatment and Control Group — A potential concern regarding our identification strategy relates to unobserved changes in the post-event period unrelated to the event year. To test for the presence of such a confound, we estimate the baseline model for the quantity

specification using a placebo treatment design in which we assigned 2020 as the treatment year. Panel (a) of Appendix Figure A.3 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 (b). Instead of relying on containerized 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 U.S.-China 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 U.S.-China trade war.

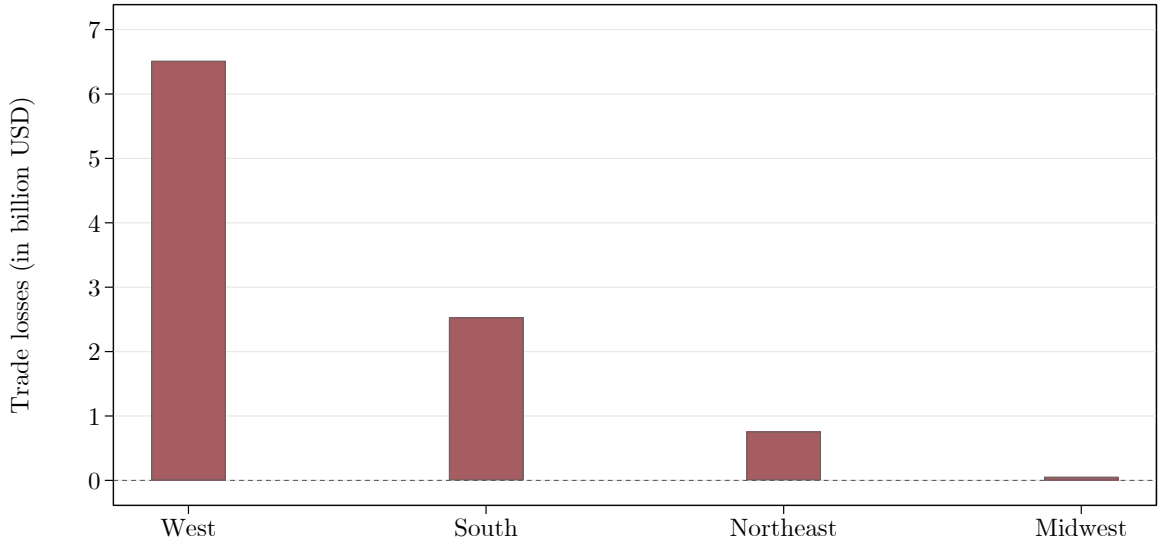
4.3 Geographic Heterogeneity

Regional Trade Effects — Figure 4 shows that the average trade effects and overall export losses vary widely across U.S. geographic regions. We classified all U.S. ports according to the U.S. customs and border region they belong to (United States Customs and Border Protection, 2020). We adjusted the baseline model by interacting the event-time coefficients with the customs and border 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.[7] The adverse trade effects are most significant for Western and Northeastern port regions. However, these average post-event trade effects are statistically indifferent to those estimated for Southern ports. Panel (b) in Figure 4 shows that the average trade effects translate into significant export losses. We assumed constant unit prices for April 2021 (the pre-event month) to estimate the trade losses

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



(a) Average trade effects.



(b) Export losses.

Figure 4: Average post-event trade effects and overall export losses by U.S. customs and border region.

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 $(\exp(\bar{\beta}_k) - 1) * 100$ based on the quantity specification. Export losses were calculated based on constant unit values for April 2021.

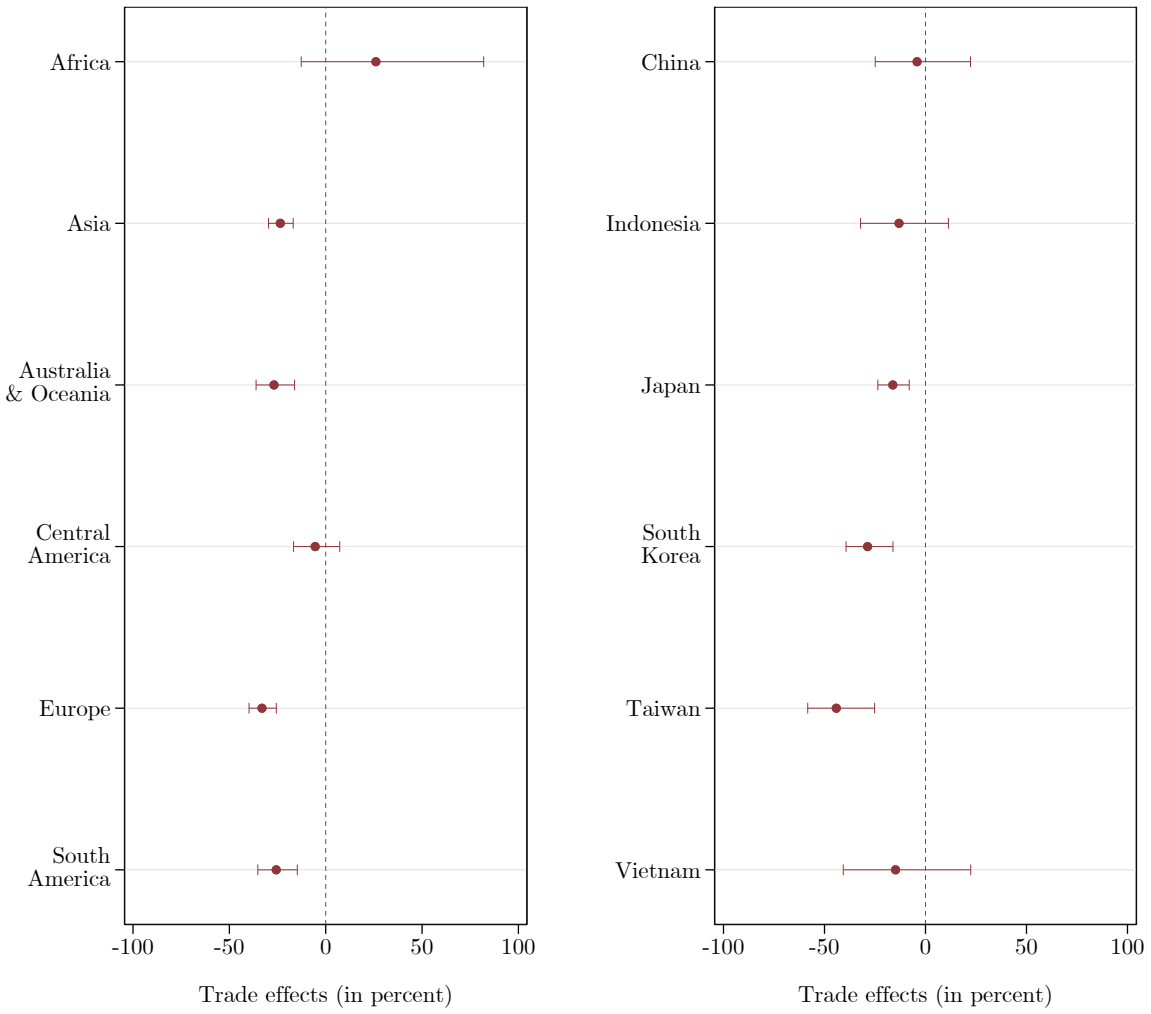
by U.S. customs and border regions based on the regional dynamic post-event treatment effects. Because we find no significant treatment effects for the unit value specification after controlling for linear pre-trends, the pre-event unit values are a reliable measure of

the actual price level. These results suggest containerized agricultural exports from Western and Southern 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 for significant economic damages for Midwestern ports. These estimates of adverse trade effects are consistent with earlier work by Carter et al. (2021) and Steinbach (2022).

Export Destinations — We compare average post-event trade effects by export destination in Figure 5.[8] Panel (a) shows that containerized agricultural exports from U.S. ports contracted the most on the route to Europe (-33 percent), Australia and Oceania (-27 percent), and South America (-26 percent). Exports to Asia (-24 percent) and Central America (-5 percent) fell less, while we find no evidence of adverse trade effects for Africa. However, the estimated trade losses reveal a different picture. We find that containerized agricultural exports to Asia contracted by almost 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 significantly smaller. Panel (b) distinguishes average post-event trade effects by major export destination in Asia. We selected the top six destinations based on the export value in the pre-treatment month (April 2021). The significant reduction in containerized agricultural exports to Japan (-16 percent), South Korea (-29 percent), and Taiwan (-44 percent) drive the overall adverse trade effects. We find only limited evidence for export losses to China and Hong Kong. Zooming in on the associated trade losses, we estimate that exports to South Korea contracted the

[8] We further explore heterogeneity according to the economic development stage and income level of the destination countries in Appendix Table A.3. Comparing average post-event treatment effects for developed with developing economies in (a), we find evidence for considerable treatment differences for the quantity specification at conventional levels of statistical significance. We explore this heterogeneity further in (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 than middle and low income. We find no evidence of significant post-event treatment effects for those countries at the lower end of the income distribution. These results underpin our observation that containerized agricultural exports to richer countries were more affected by global shipping container disruptions.

most, dropping by USD 1.4 billion, followed by Japan (USD -1 billion) and Taiwan (USD -0.9 billion). Overall, these trade impact estimates provide strong evidence for substantial geographic heterogeneity in the trade effects and export losses.



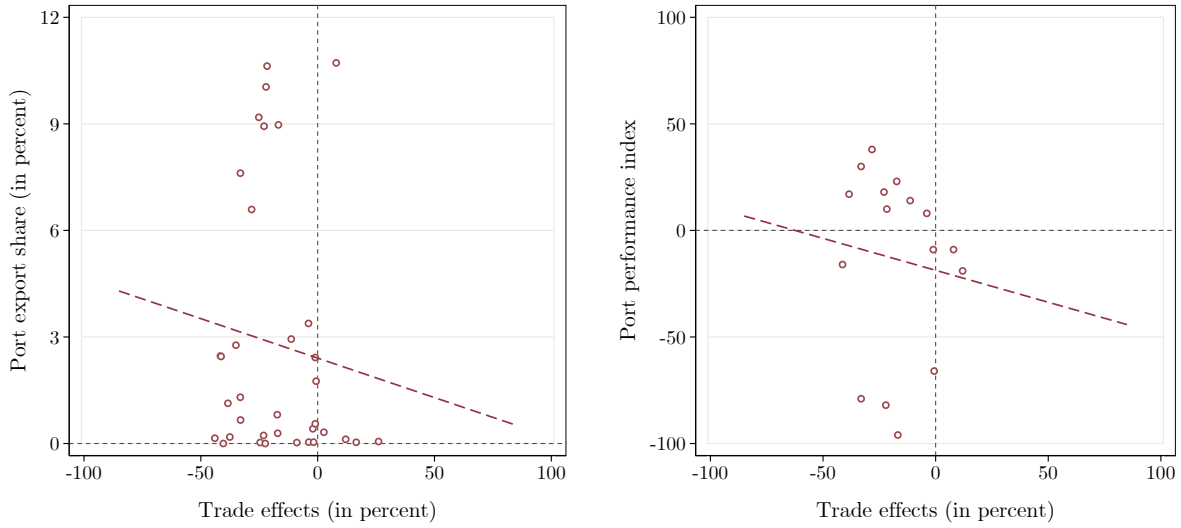
(a) Continent. (b) Asian export destinations.

Figure 5: Average post-event trade effects by continent and major Asian export destination.

Note. We excluded North America from (a) because the majority of trade with Canada and Mexico takes place via land. We selected the top six Asian export destinations based on the pre-event months in (b).

Port Size and Performance — We investigate the association between average post-event trade effects, port size, and port performance in Figure 6. Panel (a) plots the trade effects against the export share. We defined the export share based on a port's share in overall

containerized agricultural exports during the pre-event period. The data indicate a distinct pattern. Eight ports are responsible for 73 percent of all containerized agricultural exports. Apart from Houston, TX, all critical ports experienced export losses between 17 and 33 percent. In contrast, the trade effects for non-major ports vary more widely between -44 and 26 percent. Thes results indicate that agricultural exporters redirected containerized exports to other ports that significantly expanded their containerized agricultural shipments. For instance, Port Hueneme, CA, expanded its agricultural exports by 12 percent, while Houston, TX, and Panama City, FL, grew their agricultural exports by 8 percent and 26 percent, respectively. Overall, we find evidence for a negative relationship between the port



(a) Port size.

(b) Port performance.

Figure 6: Average post-event trade effects, port size, and port performance.

Note. We defined port size as the share of each port in the overall U.S. export value of contanerized agricultural products during the pre-event months. Port performance is measured by the adminstrative port performance index in the 2020 container port performance report (World Bank and IHS Markit, 2022). The overlaid dashed line represents the linear fit.

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

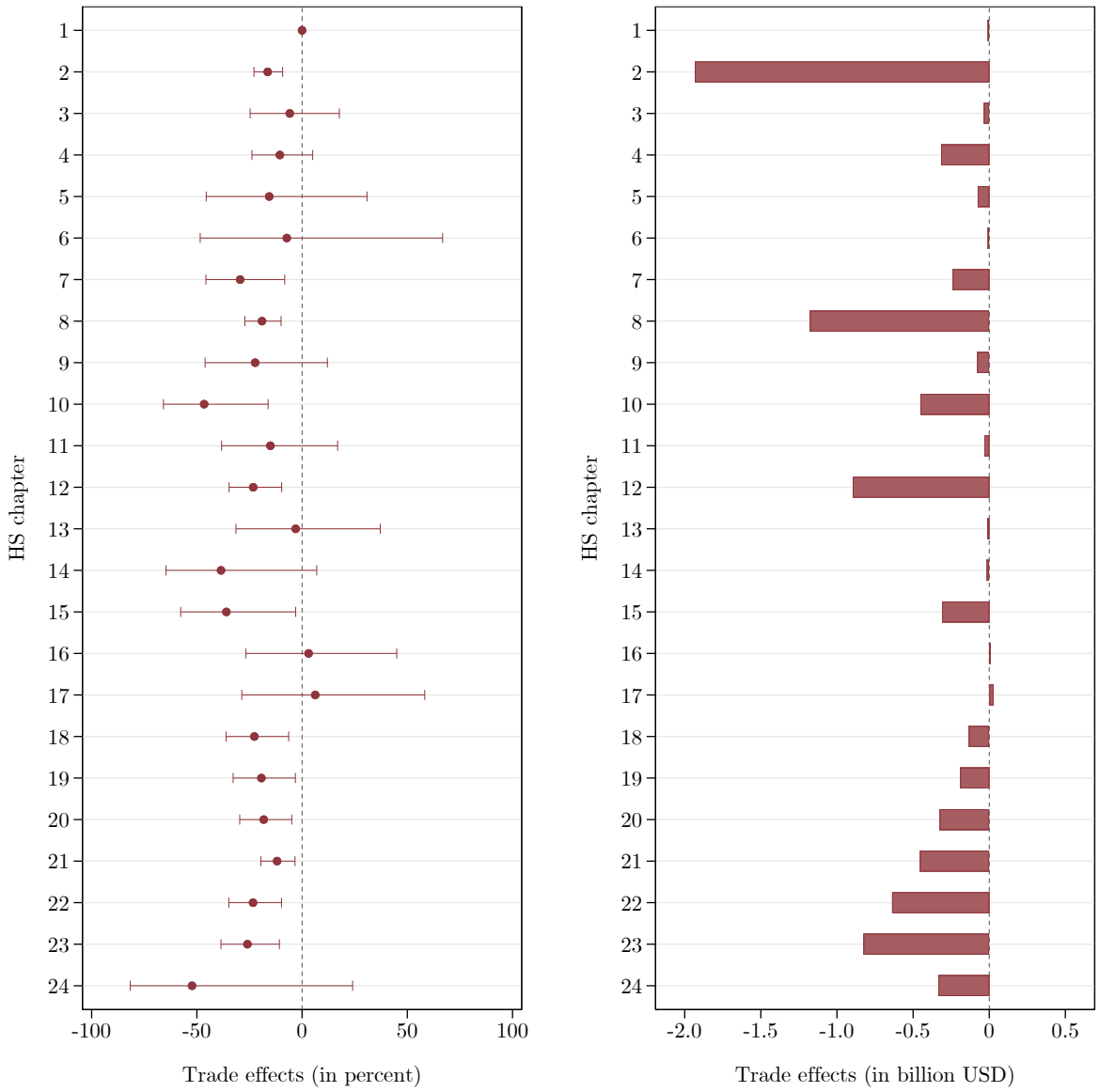
(2022).[9] We find limited evidence of a significant relationship between the port performance index and the average post-event trade effects. Again, we see two distinct groups ranked above and below the zero line for the port performance index. In addition, the average post-event trade effects for both groups are indistinguishable from one another at conventional levels of statistical significance. These results show that the relative performance within the group of U.S. ports for which reliable information on port performance is available does not explain the trade losses.

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 7. The estimated trade effects at the HS chapter level provide evidence for consistent and considerable adverse consequences of global shipping container disruptions across product groups. As shown in panel (a), in relative terms, tobacco products (chapter 24, -52 percent) experienced the most significant adverse trade effects, followed by cereals (chapter 10, -47 percent) and vegetable plaiting materials (chapter 14, -39 percent). In contrast, we find evidence of positive trade effects for sugars and sugary preparations (chapter 17, 6 percent) and meat preparations (chapter 16, 3 percent). Interestingly, (b) shows that the percentage trade effects do not translate into equally significant trade losses. As presented in panel (b), 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 containerized 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

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

insignificant at conventional levels of statistical significance, we conclude that global shipping container disruptions did not benefit trade in any particular product group while causing adverse but heterogeneous trade effects across commodity groups.



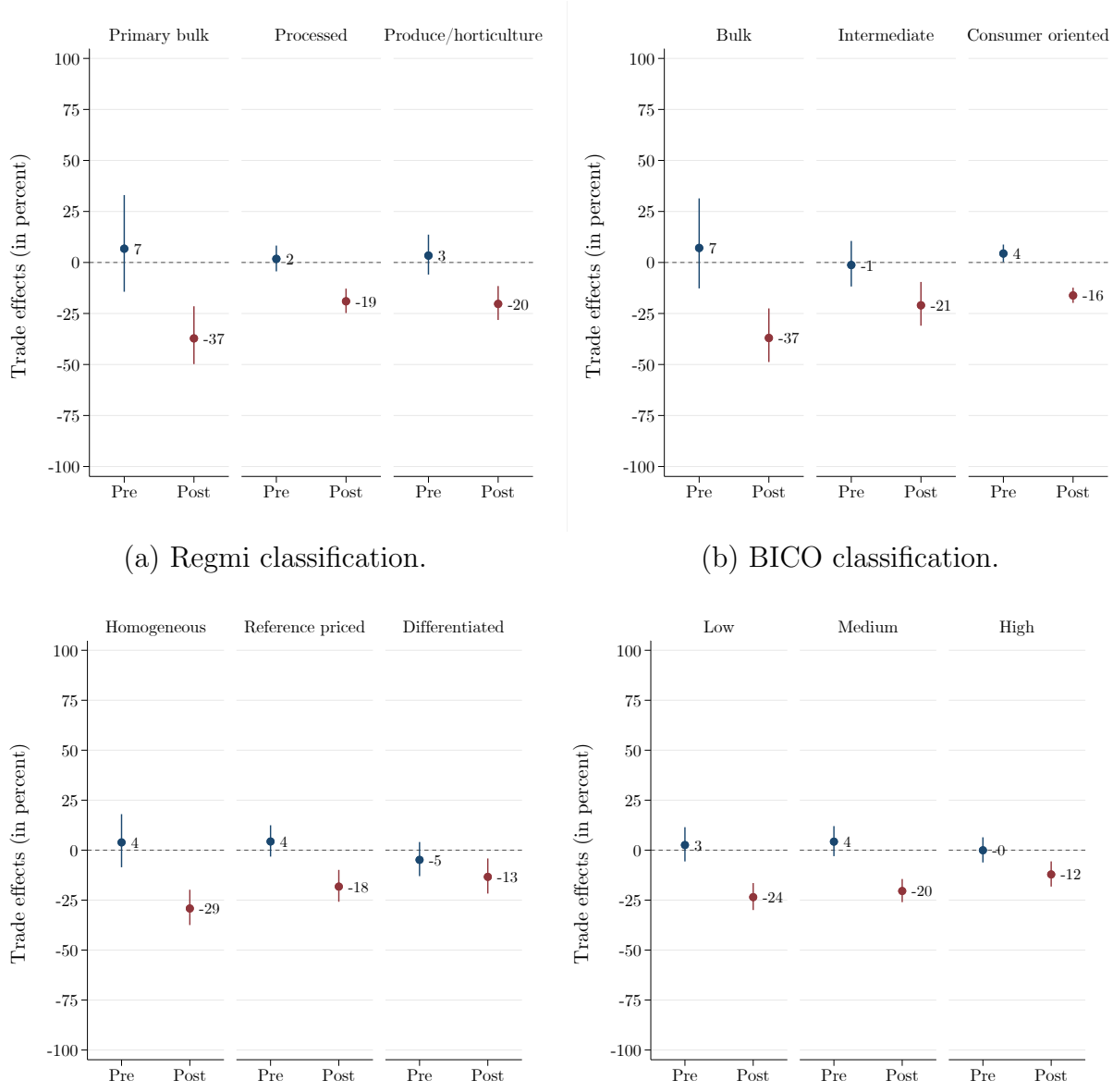
(a) Average trade effects.

(b) Export losses.

Figure 7: HS chapter level average post-event trade effects and estimated export 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 $(\exp(\bar{\beta}_k) - 1) * 100$ based on the quantity specification at the HS chapter (two-digit) level. Export losses were calculated based on constant unit values for April 2021.

Average Trade Effects by Product Classification — We compare the average post-event trade effects for four product classifications in Figure 8. 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 most significant for the bulk category (-37 percent). Processed products and horticulture/produce experienced a trade decline of about -20 percent. 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 significant adverse trade effects, while these effects are more minor for intermediate (-21 percent) and consumer-oriented products (-16 percent). Next, we used the classification by Rauch (1999) to distinguish between homogenous and differentiated products in panel (c). The results indicate more significant adverse trade effects for homogeneous (-29 percent) than differentiated products (-13 percent). 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 of that observed for products with a low unit value. This product heterogeneity indicates that exporters substituted containerized agricultural exports with a low unit value with products of higher unit value.



(a) Regmi classification.

(b) BICO classification.

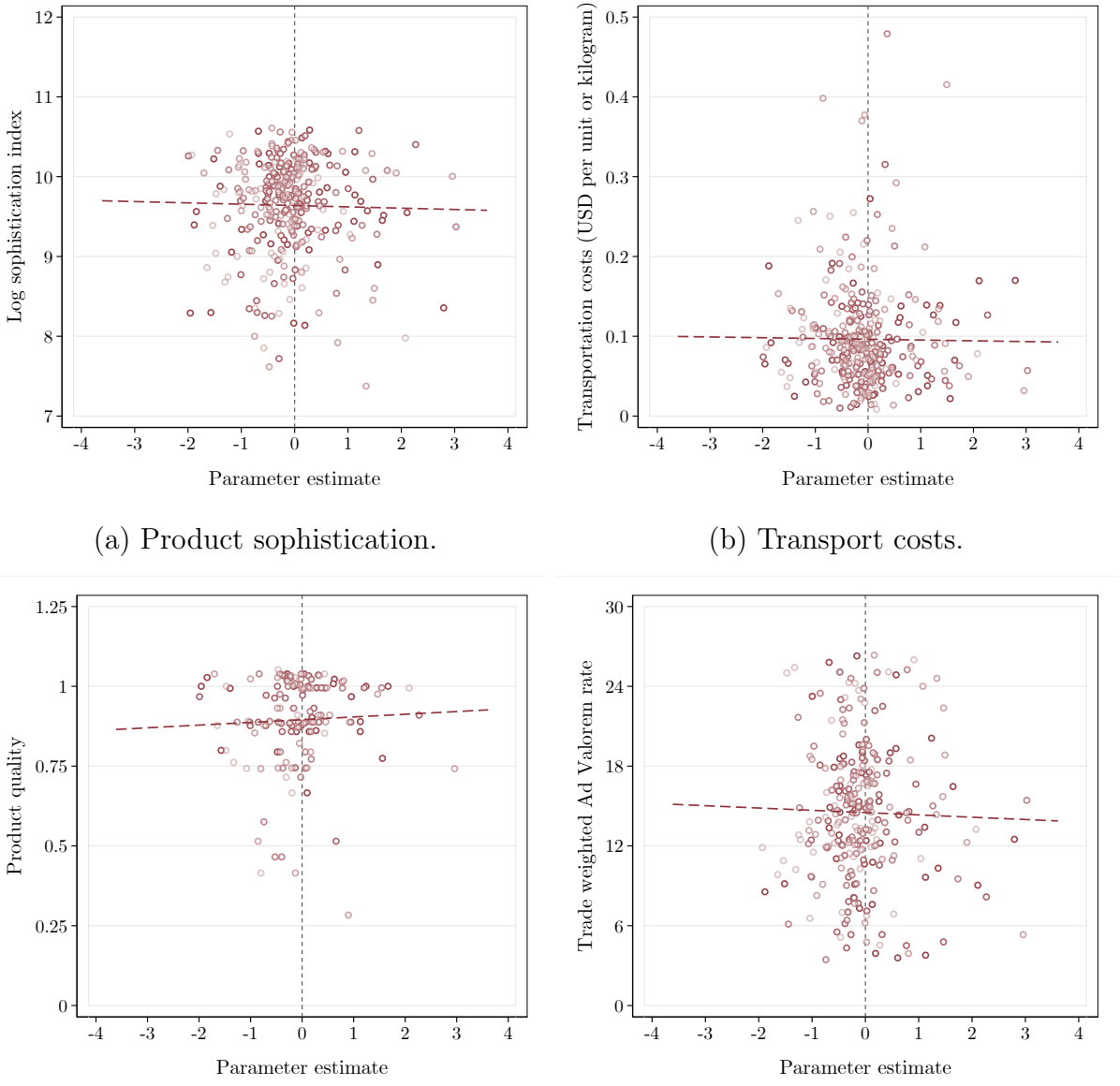
(c) Rauch classification.

(d) Price level.

Figure 8: Average pre and post-event trade effects by product classification.

Note. We calculated average trade by four product classifications. We used the classification of agricultural products by Regmi et al. (2005) and combined processed and semi-processed products in (a). Panel (b) shows differences according to the BICO classification of agricultural products (Foreign Agricultural Service, 2022), while panel (c) presents estimated trade effects for the Rauch classification (Rauch, 1999). We classified all agricultural products according to the price level in the pre-event months into low, medium, and high unit values in (d) using tertiles of the unit value distribution.

Product Characteristics — Figure 9 investigates potential product characteristics that could drive the observed treatment heterogeneity. Panel (a) correlates the product sophistication index by Hausmann et al. (2007) with the average post-event treatment effects estimated at the product level. The product sophistication index ranks traded products according to their implied productivity. We overlaid a dashed linear fit line. The fitted line does not indicate a systematic relationship between product sophistication and the treatment effects of global shipping container disruptions. Panel (b) looks at the average transport costs by product. We used trade-weighted U.S. maritime transport costs by the export destination following the approach outlined in UNCTAD (2022). Again, we find limited evidence for a significant correlation between product-level transport cost and the observed average post-event treatment effects. Panel (c) investigates the role of product quality. We used the normalized 2014 export quality index for the United States published by the IMF (2022). We find no indication of a significant association between export quality and the observed trade response. Lastly, we correlate the average post-event treatment effects with the product-level export tariff that U.S. exporters face in foreign markets in (d). We used pre-event exports to calculate the trade-weighted average export tariff at the product level. The tariff data for this analysis comes from the Consolidated Tariff Schedules (CTS) database (World Trade Organization, 2022). The linear fit proves that products with a higher average tariff level faced the same adverse post-event treatment effects. These results show that product characteristics have a limited influence on the observed trade effects. A potential explanation for this pattern is that empty containers were not going to the higher bidder. Because shipping containers are often contracted in advance, the cancellation of contracts was characterized by a degree of randomness independent of the product characteristics.



(a) Product sophistication.

(b) Transport costs.

(c) Product quality.

(d) Export tariff level.

Figure 9: Average post-event trade effects against product sophistication and transport costs.

Note. The product sophistication index in panel (a) comes from Hausmann et al. (2007). The index ranks trade goods according to their implied productivity and captures factors that determine a country's export basket. The assumption is that the higher the average income of the exporting countries, the more sophisticated the exported product. Product-specific export transport costs in panel (b) are trade-weighted transport costs by export destination measured at the product level. We used transportation and export data for 2016 from the UNCTAD (2022) to calculate the measure of product-level transport costs. The export quality index in panel (c) comes from the IMF (2022). The index is normalized, with a value of one representing a quality level in line with the world frontier, and we use the last available index from 2014. We derived the export tariff level in panel (d) from the CTS database (World Trade Organization, 2022). We weighted trade at the product level by destination to obtain the average tariff level U.S. exporters faced in export markets in 2021. The overlaid dashed line represents the linear fit.

5. Conclusions

We used a non-linear panel event study with high-dimensional fixed effects to assess the trade effects of the 2021 global shipping container disruptions on U.S. containerized agricultural exports. Our empirical strategy identifies the dynamic treatment 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 treatment effects. The baseline results show that the volume of U.S. containerized agricultural exports was 22 percent below the counterfactual from May 2021 to January 2022. The adverse trade effects translate into USD 10 billion in export losses. Western and Southern U.S. ports were the most adversely affected and experienced aggregated export losses of USD 6.5 billion and USD 2.5 billion, respectively. The product heterogeneity analysis reveals significant 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-U.S. trade war by far.

The paper expands on earlier work concerned with the adverse trade effects of the coronavirus pandemic (e.g., Arita et al., 2021; Verschuur et al., 2021a,b; Arita et al., 2022). These studies showed that global agricultural trade decreased by 7 to 9 percent in 2020 compared to the counterfactual level and revealed considerable heterogeneity across countries and product groups. However, fewer studies are concerned with the impact of global shipping container disruptions on trade flows. Our research expands on the initial California-specific impact assessment by Carter et al. (2021), the qualitative analysis by Kent and Haralambides (2022), and the U.S.-wide assessment of aggregated trade flows by Steinbach (2022). We contribute to this literature by measuring the trade effects of global shipping container disruptions and revealing heterogeneity across geographic regions and product groups. A potential 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 (e.g., 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 shipping container disruptions through their adverse effects on U.S. containerized agricultural exports.

We also contribute to the growing literature concerned with the dynamic response of international markets to trade policy shocks. By combining high-frequency trade data, an event study design, and high-dimensional fixed effects models, we utilize a novel method to measure the dynamic impact of trade shocks with limited information about 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 a counterfactual or construct synthetic control units from (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, with its focus on the response to trade shocks. These shocks are often characterized by considerable treatment dynamics over time (e.g., Amiti et al., 2021; Malgouyres et al., 2021; Ding et al., 2022; Ahn and Steinbach, 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 (e.g., Grant and Lambert, 2008; Grant and Boys, 2012; Breinlich et al., 2021; Arita et al., 2022; Curzi and Huysmans, 2022; He, 2022).

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Online Appendices

Figure A.1: Export losses over time measured in TEUs and value.

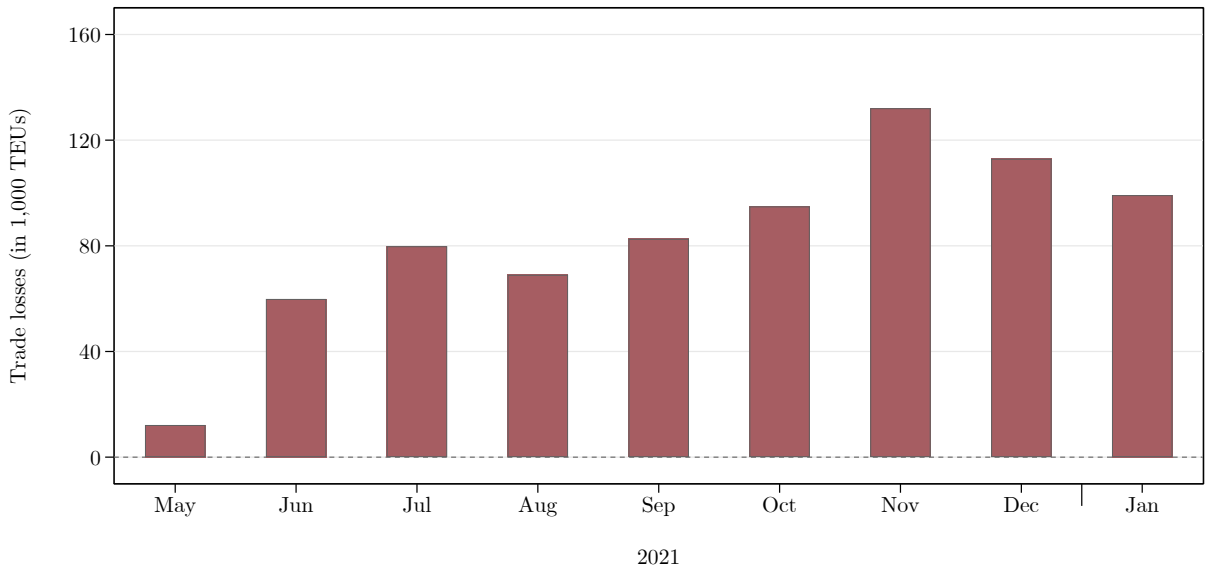
Figure A.2: Alternative approaches to dealing with zero trade flows.

Figure A.3: Placebo treatment and different control group.

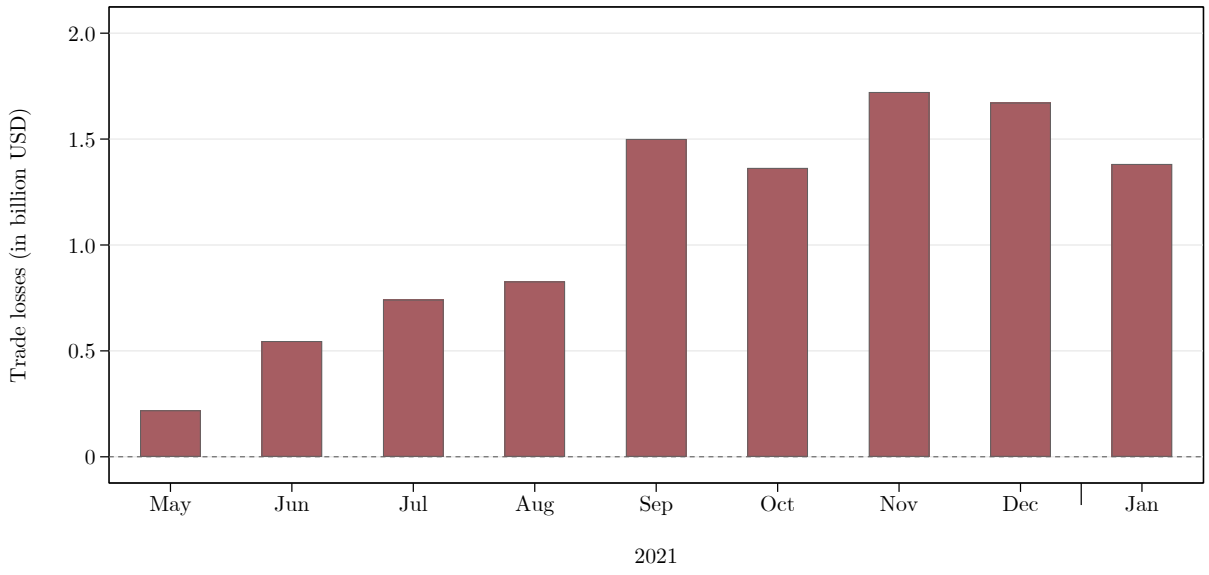
Table A.1: Average post-event treatment effects for different fixed effects structures.

Table A.2: Average treatment effects according for different data aggregations.

Table A.3: Average post-event treatment effects according to the economic development stage and income level of the destination country.



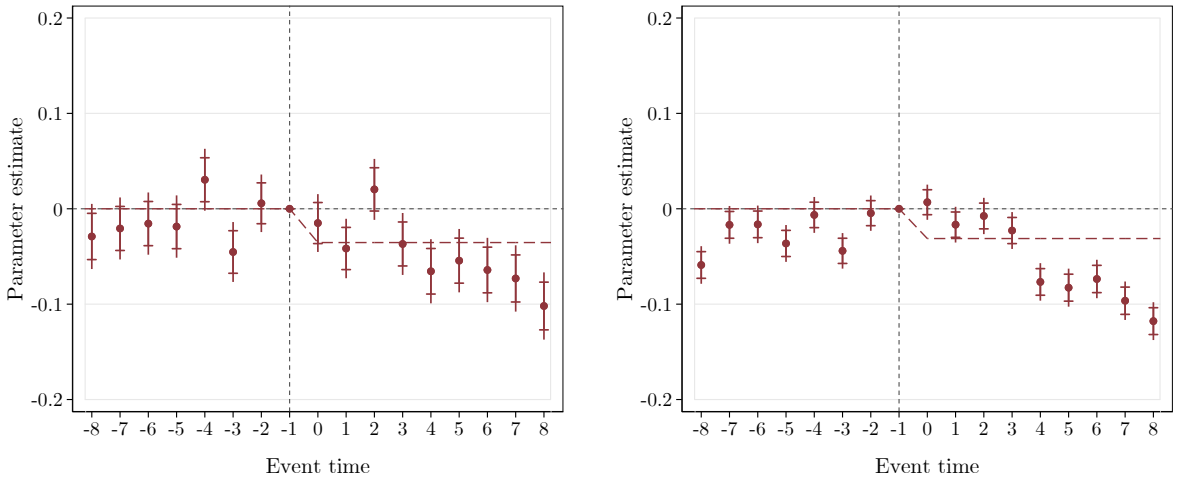
(a) TEUs.



(b) Value.

Figure A.1: Export losses over time measured in TEUs and value.

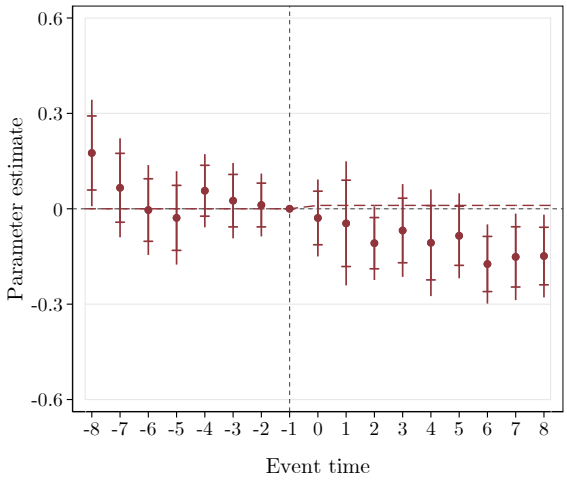
Note. The trade losses in TEUs presented in (a) were estimated using dynamic treatment effects for the TEUs specification and TEUs in the pre-event months. We used constant unit values for April 2021 and dynamic treatment effects for the quantity specification in (b).



(a) Linear regression. (b) Inverse hyperbolic sine transformation.

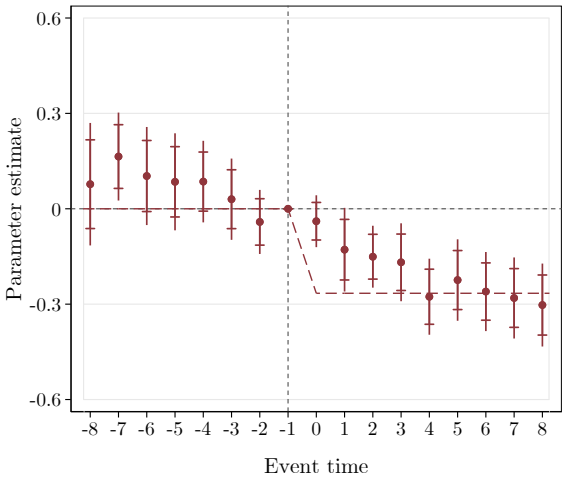
Figure A.2: Alternative approaches to dealing with zero trade flows.

Note. We dropped zero observations for the quantity specification in (a) and estimated the relationship using a linear regression model. Panel (b) shows linear regression results using the inverse hyperbolic sine transformation following the approach outlined by Bellemare and Wichman (2020).



Pre-trends p-value: 0.261 -- Leveling off p-value: 0.940 -- Static effect p-value: 0.765
Pseudo R-squared: 0.930 -- Observations: 1,945,803

(a) Placebo treatment.



Pre-trends p-value: 0.099 -- Leveling off p-value: 0.516 -- Static effect p-value: 0.000
Pseudo R-squared: 0.945 -- Observations: 1,382,112

(b) Different control group.

Figure A.3: Placebo treatment and different control group.

Note. We used 2020 as the placebo treatment in (a) and export data for 2016 to 2020 as a different control group in (b).

Table A.1: Average post-event treatment effects for different fixed effects structures.

	Value	TEUs	Quantity	Unit Value
(a) ijs#yr, ijs#mo				
Post-event average	-0.121***	-0.372***	-0.250***	0.028***
	(0.021)	(0.046)	(0.035)	(0.005)
Observations	1,934,930	1,344,389	1,934,930	705,092
Pseudo/Adjusted R-squared	0.921	0.896	0.931	0.844
(b) ijs, js#mo, is#mo, js#yr, is#yr				
Post-event average	-0.106***	-0.350***	-0.227***	0.019***
	(0.020)	(0.041)	(0.034)	(0.006)
Observations	4,260,268	3,224,162	4,260,268	949,174
Pseudo/Adjusted R-squared	0.895	0.877	0.904	0.819
(c) ij#mo, is#mo, js#mo, ij#yr, is#yr, js#yr				
Post-event average	-0.116***	-0.360***	-0.232***	0.014**
	(0.021)	(0.042)	(0.036)	(0.006)
Observations	5,283,269	3,670,814	5,283,269	953,986
Pseudo/Adjusted R-squared	0.881	0.857	0.890	0.778
(d) ij, i#mo, j#mo, s#mo, i#yr, j#yr, s#yr				
Post-event average	-0.068***	-0.309***	-0.183***	0.019***
	(0.020)	(0.037)	(0.032)	(0.005)
Observations	8,476,700	7,842,397	8,476,700	1,120,669
Pseudo/Adjusted R-squared	0.509	0.572	0.590	0.658

Note. Average post-event treatment effects were calculated using the approach outlined by de Chaisemartin and D'Haultfœuille (2020). All standard errors are adjusted for within cluster correlation at the port-destination-product level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence level, respectively.

Table A.2: Average treatment effects according for different data aggregations.

	Value		TEUs		Quantity		Unit Value	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Port-destination-product	-0.027	-0.121***	0.033	-0.372***	0.025	-0.250***	-0.029***	0.028***
	(0.019)	(0.021)	(0.030)	(0.046)	(0.033)	(0.035)	(0.005)	(0.005)
Observations	1,934,930		1,344,389		1,934,930		705,092	
Pseudo/Adjusted R-squared	0.921		0.896		0.931		0.844	
Port-product	-0.061***	-0.076***	0.032	-0.300***	0.012	-0.195***	-0.015*	0.025***
	(0.018)	(0.022)	(0.022)	(0.042)	(0.028)	(0.034)	(0.009)	(0.008)
Observations	431,329		352,227		431,329		253,619	
Pseudo/Adjusted R-squared	0.969		0.959		0.968		0.845	
Country-port	-0.060***	-0.061**	0.004	-0.305***	0.008	-0.177***	-0.043**	0.060***
	(0.022)	(0.026)	(0.028)	(0.049)	(0.030)	(0.037)	(0.017)	(0.017)
Observations	144,124		96,617		144,124		95,883	
Pseudo/Adjusted R-squared	0.972		0.962		0.963		0.629	
Port-destination	-0.056***	-0.098***	-0.000	-0.303***	0.009	-0.217***	-0.031***	0.025***
	(0.020)	(0.022)	(0.036)	(0.056)	(0.042)	(0.045)	(0.006)	(0.008)
Observations	997,148		701,039		997,148		509,269	
Pseudo/Adjusted R-squared	0.957		0.943		0.961		0.841	

Continues on next page.

Table A.2 – Continued from previous page.

	Value		TEUs		Quantity		Unit Value	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Port	-0.093***	-0.061	-0.003	-0.267***	-0.006	-0.162***	-0.020	0.053
	(0.024)	(0.040)	(0.026)	(0.062)	(0.035)	(0.039)	(0.068)	(0.065)
Observations	4,446		2,448		4,446		3,543	
Pseudo/Adjusted R-squared	0.994		0.988		0.988		0.741	
Destination	-0.072***	-0.053*	0.000	-0.237***	0.006	-0.167***	-0.033	0.085***
	(0.019)	(0.030)	(0.024)	(0.070)	(0.032)	(0.044)	(0.029)	(0.026)
Observations	13,536		9,519		13,536		12,099	
Pseudo/Adjusted R-squared	0.993		0.988		0.986		0.713	
Product	-0.081***	-0.070***	0.010	-0.249***	0.005	-0.175***	-0.021	0.028*
	(0.022)	(0.024)	(0.034)	(0.051)	(0.033)	(0.034)	(0.017)	(0.016)
Observations	50,600		48,790		50,600		42,411	
Pseudo/Adjusted R-squared	0.986		0.986		0.987		0.894	

Note. Average pre-event and post-event treatment effects were calculated using the approach outlined by de Chaisemartin and D'Haultfœuille (2020). All standard errors are adjusted for within cluster correlation at the aggreation unit level. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent confidence level, respectively.

Table A.3: Average post-event treatment effects according to the economic development stage and income level of the destination country.

	Value	TEUs	Quantity	Unit Value
(a) Economic development				
Developed economies	-0.351***	-0.243***	-0.146***	0.021*
	(0.047)	(0.036)	(0.034)	(0.012)
Developing economies	-0.297***	-0.213***	-0.087***	0.031***
	(0.064)	(0.046)	(0.027)	(0.006)
Observations	1,344,389	1,934,930	1,934,930	705,092
Pseudo/Adjusted R-squared	0.896	0.930	0.921	0.844
(b) Income group				
High income	-0.431***	-0.273***	-0.131***	0.024***
	(0.041)	(0.036)	(0.027)	(0.008)
Upper-middle income	-0.248**	-0.148*	-0.083*	0.026**
	(0.117)	(0.081)	(0.047)	(0.011)
Lower-middle income	-0.015	-0.218***	-0.085*	0.042***
	(0.123)	(0.080)	(0.049)	(0.013)
Low income	0.597**	-0.065	0.028	0.051
	(0.276)	(0.191)	(0.153)	(0.047)
Observations	1,344,389	1,934,930	1,934,930	705,092
Pseudo/Adjusted R-squared	0.896	0.931	0.921	0.844

Note. Average pre-event and post-event treatment effects were calculated using the approach outlined by de Chaisemartin and D'Haultfœuille (2020). Data for the economic development stage comes from the United Nations (2022) and for the income level from the World Bank (2022). All standard errors are adjusted for within-cluster correlation at the port-destination-product level. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent confidence level, respectively.