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THE ELASTICITY OF SUBSTITUTION BETWEEN TRANSPORTATION MODES: EVIDENCE FROM RUSSIA'S BLOCKADE OF UKRAINE'S PORTS

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We thank the editors Oleksandr Talavera, Yurii Gorodnichenko and Vitaliia Yaremko and three anonymous referees for their constructive comments and suggestions. We also thank Oleg Badunenko, Udo Kreickemeier, Tymofii Mylovanov, as well as the participants of the 27th Göttingen Workshop "International Economic Relations", the Economic Modelling 2025 Conference "Ukraine: Economic Insights for Future Policy Actions", and BOFIT seminar for valuable comments and suggestions. Expressed views and mistakes are the sole responsibility of the authors.

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ABSTRACT

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JEL CLASSIFICATION: F14, F51, R41, R11, R12

KEYWORDS: international trade, supply chains, mode of transportation, blockade

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Abstract

This paper estimates the elasticity of substitution between transport modes when maritime access is disrupted at scale, using Russia's blockade of Ukraine's Black Sea and Azov Sea ports as a natural experiment. We combine Trade Data Monitor customs records for 2019-2025 with an index of conflict intensity around Ukrainian ports constructed from geolocated war-related events, and estimate the mapping from that index onto observed relative sea-to-land freight costs. The implied elasticity of substitution is 2.25 to 2.36, with a range of 1.9 to 3.7 across specifications. Substitution was concentrated in the first months after the invasion and among destinations at intermediate distances. The response is largest where both modes were genuinely available before the war, not where maritime dependence was highest. It falls after the first months as successive corridor arrangements restored partial maritime access, which identifies the reversibility of modal shifts once the disrupted mode returns.

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1. Introduction

Product diversification without transport-mode diversification is incomplete resilience. An economy that exports a thousand goods through a single transport mode or a single port remains acutely exposed when that corridor closes. Yet the parameter governing this exposure, the elasticity of substitution between transport modes, is rarely estimated directly, and the standard account of trade resilience as diversification across products and markets largely overlooks it.

The gap matters most for quantitative trade models in the tradition of Eaton and Kortum (2002) and Caliendo and Parro (2015), where transport costs shape equilibrium trade flows and welfare, and where counterfactual predictions are sensitive to the degree of substitutability across modes. In the absence of credible estimates, this parameter is calibrated from assumed values or inferred from aggregate data that obscure the underlying adjustment mechanism. Such estimates are scarce because transport costs, infrastructure, and mode choice are jointly determined. Infrastructure is placed where traffic is expected (Duranton and Turner 2012), the characteristics of traded goods shape which mode they use (Hummels and Schaur 2013), and transport conditions in turn shape specialization (Harrigan 2010). Identifying substitution across modes from observed trade flows alone is therefore difficult, as studies of transport technology adoption have had to address the same joint determination (Bernhofen, El-Sahli, and Kneller 2016; Coşar and Demir 2018), and what is needed instead is a large change in the availability of one mode that is unrelated to the goods being shipped.

This paper estimates the *elasticity of substitution between maritime and land transport* using the Russian blockade of Ukraine’s Black and Azov Sea ports as a natural experiment. From 24 February 2022, Ukraine lost access to the maritime routes carrying roughly two-thirds of its export value. The blockade was sudden, comprehensive, and, unlike the short-lived disruptions that identify most existing estimates, sustained over years rather than months, forcing exporters to reallocate shipments toward rail and truck corridors. Moreover, it was not a single on-off event: the Black Sea Grain Initiative of July 2022 partially restored maritime access, Russia’s withdrawal a year later removed it again, and Ukraine’s unilateral corridor from August 2023 reopened it under Ukrainian control. The resulting variation in the intensity of disruption, across regions and over more than three and a half years, identifies the coefficient we translate into the implied elasticity, and it lets us trace both the immediate response and the subsequent adjustment as maritime access was partially restored.

We compile a monthly dataset on Ukrainian exports over 2019–2025 from Trade Data Monitor, which draws on official trade statistics. Beyond the standard destination, value and quantity fields, it records the mode of transport, the product at the 10-digit level of the Ukrainian classification (UKTZED), and the region of origin within Ukraine. We combine pre-war differences in reliance on maritime transport with a monthly index of war-related events near Ukraine’s ports, mapped to regions of origin, to implement a shift-share design (see, e.g., Goldsmith-Pinkham, Sorkin, and Swift 2020; Borusyak, Hull, and Jaravel 2022). Intuitively, export relationships that depended more heavily on maritime transport before the war experienced a larger effective shock as strikes intensified around the ports they had relied on. This differential exposure allows us to trace how much lost maritime trade was reallocated to rail and truck. Estimating the mapping from the conflict index onto observed relative sea-to-land freight costs translates the estimated coefficient into an elasticity of substitution. Fixed effects at the product–origin–destination level, together with product-, origin- and destination-specific period effects, absorb common shocks to trade at each of these levels, and we report elasticities at both the aggregate and sectoral levels, testing additionally for the compounding effects of production disruptions.

We find the elasticity of substitution between transportation modes to be 2.25 for values and 2.36 for quantities, with a range of 1.9 to 3.7 across specifications. Modes are therefore substitutes, imperfect but substantial ones: overland routes absorbed a meaningful part of the maritime disruption, although the land margin expanded by only about a quarter as much as maritime shipments fell. The composition of the response matters as much as its size. Road crossings into the European Union were the primary margin of adjustment for grains and oilseeds, whereas rail carried more of the response for bulk industrial goods such as minerals and base metals. Substitution is largest where both modes were genuinely available before the war. Sections that shipped almost everything by sea are bulk agricultural commodities for which overland routes could absorb only part of the volume at comparable cost, and they show implied elasticities of about 2.0, while sections that were already shipped overland had little to reallocate. The largest responses, 3.6 for minerals and 5.0 for base metals, come from the middle of the exposure distribution, where an alternative existed but was not already dominant. An aggregate value applied uniformly would misstate disruption at both ends. Finally, the implied elasticity is highest at the onset of the blockade, roughly 3.3 in the first two months, and settles at about 2.3 over longer windows as successive corridor arrangements restored partial maritime access. Adjustment was front-loaded,

and what unwound was the emergency reallocation rather than a durable shift in transport technology.

Existing estimates of cross-modal substitution vary by an order of magnitude, and the spread tracks what identifies them. Closest to our design are studies exploiting capacity shocks and observed reallocation. Tolva (2026) uses the closure of Russian-Ukrainian airspace and the 2021 US West Coast port congestion to estimate air-sea substitution, recovering around 1.2 in the short run from high-frequency price variation and 1.6 to 2.3 over longer horizons. Fuchs and Wong (2025) recover elasticities near 1.1 in a multi-modal network framework, instrumenting current road capacity with historical transport plans and rail routes in the style of Duranton and Turner (2012). Ko, Nigai, and Truax (2025) estimate air-sea elasticities for 21 sectors from bilateral mode-disaggregated trade for 2016-2019, instrumenting with global mode-specific cost shocks interacted with bilateral geography, and report a pooled estimate of 2.44. Our aggregate estimate of 2.25 sits inside the interval traced by these studies, close to the pooled estimate of Ko, Nigai, and Truax (2025). We contribute with studying a different source of variation: one mode removed outright, for years, across the full product range of a national export basket, rather than made marginally more expensive.

The horizon comparison with Tolva (2026) is instructive precisely because it runs the other way. Tolva finds substitution rising with the horizon, from 1.2 in the short run to as much as 2.3, while we find it falling, from roughly 3.3 in the first two months to 2.25 over three and a half years. The difference is not a contradiction but a consequence of what happens to the disrupted mode. In Tolva (2026)'s episodes the constrained mode stays constrained while shippers progressively re-optimize, so measured substitution accumulates. In ours the blockade was partially lifted, so the emergency reallocation partly unwound. What our declining profile identifies is the reversibility of modal shifts once maritime access returns, which is a distinct object from the long-run adjustment Tolva (2026) recovers, and one that matters for how corridor closures should be modelled.

A second approach infers the elasticity from structural demand systems with cost-shifter instruments and delivers much larger values: Lugovskyy, Skiba, and Terner (2025) recover 14.3 from a nested demand inversion with CIF-charge and oil-distance instruments. Chowdhry, Heiland, and Mahlkow (2026) estimate 6.9 for substitution across vessels, a within-maritime margin rather than a cross-modal one. These identify from price variation under normal operating conditions, where reallocation is limited by cost rather than by availability, and are correspondingly less informative about what

happens when a mode disappears.

Ko, Nigai, and Truax (2025) further show in general equilibrium that accounting for sectoral heterogeneity in mode substitution materially changes counterfactual outcomes relative to a uniform-elasticity calibration, documenting a range from near zero to 11.4 with high value-to-weight sectors most responsive. We find heterogeneity of the same character across Ukrainian sections, with statistically-significant full-window elasticities from about 1 to 5 among sections with a meaningful pre-war maritime margin, though ordered differently: substitution peaks where both modes were genuinely available before the war rather than rising monotonically in maritime dependence. This motivates the sectoral estimates in Section 6.

Our contribution is to deliver empirically grounded elasticities, aggregate and sectoral, from a setting where one mode was removed rather than made marginally more expensive. These discipline quantitative trade models with mode-specific transport costs and CES transport aggregators, improving counterfactual analysis of corridor closures, infrastructure investment, and logistics diversification. The Ukrainian context is specific, but unusually favorable to substitution: land borders with four EU member states and Moldova, an extensive road network, substantial pre-existing trucking capacity, and an accommodating policy environment. If adaptation remains this incomplete under these conditions, and does not strengthen over three and a half years, economies with fewer overland alternatives should expect less.

The rest of the paper proceeds as follows. Section 2 describes the data, the port-blockade index, and the freight cost measures. Section 3 outlines the empirical strategy, connecting the structural model to the estimating equations. Section 4 examines pre-trends and documents the partial switch of maritime-dependent export spells from sea to land transport. Section 5 presents the aggregate implied elasticities together with sensitivity checks, including a set of tests distinguishing transport disruption from wartime production disruption. Section 6 examines sectoral heterogeneity across HS sections. Section 7 discusses the results and concludes.

2. Data Description

2.1. Trade data

We use monthly Ukrainian export data from Trade Data Monitor (TDM) over the period January 2019-September 2025. TDM draws on the same official customs records as UN COMTRADE, but releases them with a shorter lag and reports two dimensions

absent from COMTRADE: the Ukrainian region (oblast) of origin and the mode of transportation. Each flow also records the destination country, the export value and the quantity, at the ten-digit product codes according to the Ukraine's customs tariff.

Concordance between Product Classifications. Product codes follow the Ukrainian Classification of Goods for Foreign Economic Activity (UKT ZED), a national ten-digit extension of the Harmonized System (HS). UKT ZED was revised twice within our sample window: the 2012 vintage was replaced by the 2017 vintage in July 2020, and the 2017 vintage by the 2022 vintage in January 2023. Product codes are therefore not comparable over time without harmonization.

We construct a synthetic concordance at the six-digit level from the official transition tables published by the State Customs Service of Ukraine. We truncate each ten-digit code to its six-digit HS prefix, deduplicate the resulting correspondences, and treat them as edges of an undirected graph whose nodes are six-digit codes from the three vintages. The connected components of this graph define our synthetic product identifiers (SIDs). By construction, each six-digit code belongs to exactly one SID, and codes describing the same heading under different vintages always share a SID, whether the underlying correspondence is one-to-one, one-to-many or many-to-many. Throughout the paper, *product* refers to a SID. Each SID is assigned an HS2 chapter using the six-digit code with the largest export value share within a vintage period. Where the three vintages imply the same chapter, that chapter is assigned, but where they disagree, the SID is left unclassified.

Transport modes. Each flow is recorded under one of five modes: vessel, automobile, railway, aircraft and other. In the main analysis, *land* transport is the sum of automobile and railway. Because some modes may imply intermodal movements, we construct a narrower reclassification for sensitivity analysis, reported in Table A14 in the appendix.

Sample construction. We define a spell as a unique product-destination-origin triple and measure pre-war export value as the sum of monthly exports over 2019-2021. We first drop observations with missing or undefined product code, origin, destination or transport mode, and deflate values by the US CPI with January 2022 as the base month.¹

¹Series CPIAUCSL "Consumer Price Index for All Urban Consumers: All Items in U.S. City Average" (monthly, seasonally adjusted) from FRED. Deflation affects value-based outcomes and value-based exposure measures only, while quantity-based specifications are unaffected.

We then apply three restrictions: we retain the top 100 destination countries and the top 2,000 products by pre-war export value, and drop spells whose cumulative 2019-2021 exports fall below USD 10,000. The resulting estimation sample contains 73,329 spells covering 1,999 products, 100 destinations and 25 origin regions, which yields 5,939,649 spell-month observations once the panel is balanced by filling non-trading months with zeros.

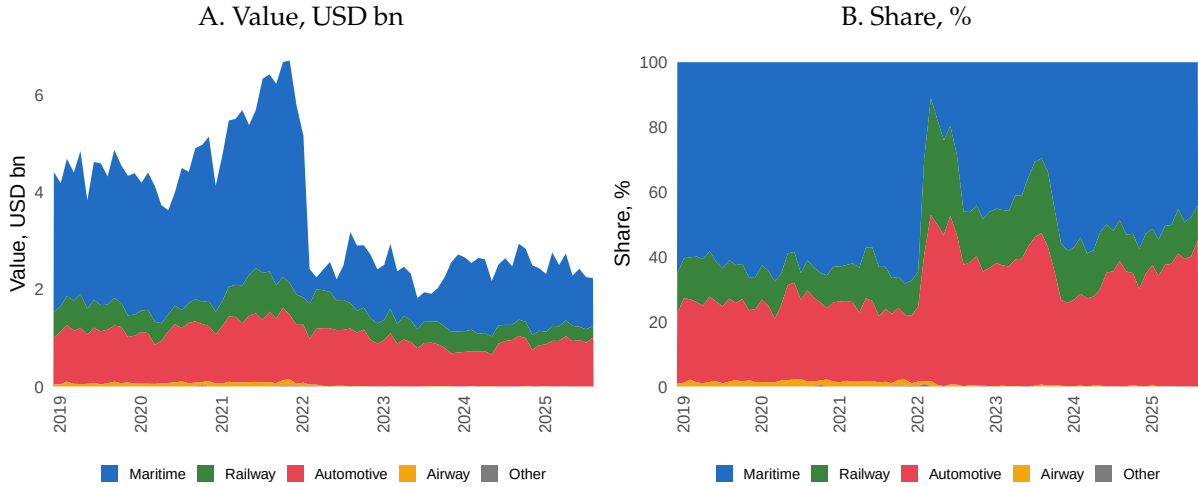
The restrictions are not costly in value terms since the estimation sample accounts for 98.8% of pre-war export value. Retained and dropped spells differ sharply in size: median pre-war exports are USD 89,513 among retained spells and USD 851 among dropped spells with any non-zero pre-war trade. Moreover, the imbalance between maritime exposure of dropped and retained export spells is mild: 25.6% of retained spells involve a vessel-exposed product-origin combination, against 31.4% of dropped spells.

Exposure measures. For each spell we measure pre-blockade dependence on maritime transport over 2019-2021 in three ways: a binary indicator for any vessel shipment, the vessel share of export quantity, and the vessel share of export value. The binary indicator is used in the baseline specification, and the two continuous measures are used for additional checks in Section 5.

Trends in the data. Figure 1 shows the value (Panel A) and modal composition (Panel B) of monthly Ukrainian exports over January 2019-September 2025. Seaborne shipments dominated before the invasion: vessels accounted for roughly two-thirds of export value, trucks for one-fifth to one-quarter, and rail for about a tenth, with air and other modes negligible.

Both panels change abruptly in February 2022. Total export value falls by close to half and does not return to its pre-war level at any point in the sample. The maritime share collapses within two months, while rail absorbs the immediate shock, with its share surging in mid-2022, and road takes over progressively thereafter. The maritime share partially recovers from August 2022 under the Black Sea Grain Initiative, falls back when the Initiative lapses in July 2023, and rises again from late 2023 following the opening of Ukraine's unilateral corridor, without regaining its pre-war dominance. The road share trends upward throughout 2023-2024, consistent with re-routing through western border crossings and logistics hubs as capacity there was built out. The overall pattern is one of pronounced but incomplete substitution away from maritime routes,

FIGURE 1. Ukraine’s merchandise exports by the mode of transportation, 2019-2025



Note: Monthly export value (deflated to January 2022 US dollars), January 2019-September 2025, aggregated by transport mode. The figure uses the estimation sample described in Section 2.

and of a return to sea transport that is partial, uneven, and reversible.

2.2. Extent of Port Blockade

Shelling of port infrastructure. Because the port blockade arose directly from the full-scale invasion, its intensity and geographic pattern reflect the underlying military campaign. We proxy the monthly severity of port disruption by measuring Russian military activity proximate to Ukraine’s Black Sea and Sea of Azov ports. The measure is defined over the full sample period, January 2019 through September 2025, and equal to zero before February 2022.

We geolocate 18 Ukrainian ports² and count war-related events within a 10-kilometer radius of each port.³ We draw on three sources of geolocated events. The primary source is VIINA 2.0 (Violent Incident Information from News Articles on the 2022 Russian Invasion of Ukraine; Zhukov and Ayers 2023; Zhukov 2023), an open-source event dataset based on automated scraping of Ukrainian and Russian media that uses a trained BERT-based classifier (Devlin et al. 2019) to geolocate and code conflict events by date, location, actor, and tactic. As supplementary sources we use the war-fire model developed by

²The list of ports is presented in Appendix C. Coordinates are collected from two sources, GeoHack and the Ukraine Logistics Dataset on the Humanitarian Data Exchange. Where both report a port we take the midpoint, and where only one does we use that one. The reconciliation is immaterial at the 10-kilometer baseline radius but not at 2 kilometers, which is one reason the narrow radius serves as a robustness check rather than the baseline.

³We also construct instruments using 5- and 2-kilometer radii.

The Economist (The Economist and Solstad 2023), which identifies war-related fires from NASA FIRMS thermal anomaly data using a probabilistic classifier, and the Ukraine Conflict Monitor from ACLED (Raleigh, Kishi, and Linke 2023), which combines media reports, official documents, and NGO sources to code events by location, actor, and event type.

Figure A.3 plots different event series, normalized to the unit interval, for the radii of 10, 5, and 2 kilometers around the ports, together with the share of the 18 ports closed in each month. Port-related events surged sharply with the onset of the full-scale invasion on 24 February 2022, marked by intense airstrikes, frequent air raid alerts, and widespread property damage in port cities including Odesa, Mykolaiv, Mariupol, and Berdiansk. Activity remained extremely high through mid-2022 as Russia sought to consolidate control over the northern Black Sea coast and secure access to the Sea of Azov. The occupation of Mariupol and other Azov ports effectively sealed off Ukraine’s eastern maritime access, while continued bombardment of Odesa and nearby infrastructure prevented normal port operations.

A notable moderation in direct strikes followed the establishment of the Black Sea Grain Initiative on 22 July 2022, which created a monitored corridor allowing limited resumption of agricultural exports from Odesa, Chornomorsk, and Pivdennyi. Property damage and fire events declined during late 2022 and early 2023, though air raid alerts and sporadic attacks persisted. This relative stabilization ended when Russia withdrew from the agreement in July 2023, triggering a renewed escalation of strikes targeting port facilities and storage infrastructure in the Odesa region. From late 2023 onward, Ukraine’s establishment of a unilateral coastal shipping corridor along the western Black Sea contributed to a gradual restoration of port operations, though the frequency of airstrikes remained elevated.

From ports to oblasts. Trade data record the oblast of origin, so we map port-level conflict to oblasts. We construct three port-month indicators from VIINA 2.0: *hits* (i.e., the number of airstrike, UAV, and artillery tactics recorded at a location and date), *airalert* (air raid alert activations), and *property* (i.e., property damage events). News reports for each of the series are de-duplicated at the event level, so the monthly figure counts distinct events rather than news reports. VIINA 2.0 also reports the number of articles behind each event, but we do not use them, since media attention is plausibly endogenous to the economic salience of the flows we study. Ports at which no event is recorded in a given month enter the panel as true zeros rather than as missing.

Each oblast then receives an inverse-distance-weighted sum of the port-level counts, with weights $w_{or} = 1/d_{or}$, where d_{or} is the distance from a centroid of oblast o to port r , clipped to Ukraine's borders. We do not normalize the weights for each oblast to be equal to unity, since then each oblast would receive a weighted *average* across the 18 ports, potentially making some distant oblasts appear more exposed to port blockade compared to the coastal ones. With non-normalized weights the index is increasing in proximity to struck ports, with Mykolaiv, Odesa, and Kherson facing the highest intensity of port blockade and the landlocked western oblasts - the lowest.

Constructing the conflict shift. The oblast-month series are standardized by their post-February 2022 standard deviation. Scaling by the full-sample standard deviation would be dominated by the February 2022 level break, since these series are essentially zero beforehand. We then summarize the standardized indicators into a single index by principal component analysis, in four variants differing in which sources enter.

In each case the PCA is fitted on the *cross-sectional* oblast means, and the resulting rotation is applied to the full panel to produce an oblast-level time series. This lets the loadings reflect how the indicators covary across oblasts, which is the variation that identifies the elasticity. Because the sign of a principal component is identified only up to a reflection, we orient each fit so that *hits* loads positively, ensuring that higher index values always mean more conflict. The projected series are then normalized within oblast by pooled post-invasion standard deviation and demeaned on the pre-invasion period, so each index is zero before the war and measured in post-invasion standard deviations thereafter. Figure A.4 shows the resulting indices.

PC1 uses the three VIINA 2.0 indicators only. At the 10-kilometer radius, PC1 explains 99% of the variance in the input variables, with all three loading positively and with similar magnitude, confirming that it captures a single underlying port blockade intensity signal. PC1 is the benchmark instrument because it relies exclusively on conflict events near ports, which are plausibly exogenous to individual trade flows.

PC2 augments the three VIINA 2.0 indicators with two ACLED event counts, kinetic military events and infrastructure attacks. *PC3* augments them instead with the war-fires series. *PC4* combines all three sources. These three variants serve as robustness checks establishing that the benchmark result is not an artefact of a single conflict data source. PC3 is informative in particular because it pairs news-based measurement (VIINA 2.0) with remote-sensed measurement (war-related fires), so correlated media-coverage error cannot drive the agreement between them. Across all four variants the loadings fall

in the range 0.40-0.58 in absolute value, close to the equal-weight benchmark, so each index reads as an intensity measure rather than as a contrast between indicator types.

Panel A of Figure A.4 shows that PC1 is stable across radii, with the 10-kilometer specification producing the cleanest signal. Panel B shows that the four indices track each other closely, with post-invasion pairwise correlations above 0.85 (the weakest pair is PC1 and PC4). Panel C plots the oblast-level PC1 series against the national aggregate, confirming that the index varies meaningfully across oblasts. This cross-regional variation is what identifies the elasticity.⁴

The indices are unit-free. Before they enter equation (14) they are rescaled onto log relative transport costs by a linear map, common across oblasts and without an intercept, since all indices are zero before February 2022 by construction. The slope of that map is estimated using the available freight cost series described in Section 2.3, while the first-stage estimates are reported in Section 3.4.

General conflict intensity. The measures described so far are deliberately local and count events within 2 to 10 kilometers of a port, so that variation in the index reflects disruption to maritime access rather than the war in general. The same sources support a broader measure, and the contrast between the two is useful. Aggregating VIINA 2.0 military events, war-related fires, and ACLED events across the entire oblast rather than around ports, yields a monthly measure of general conflict intensity on the same balanced oblast panel.⁵ War intensity measures from different sources are correlated, but they are not the same object, and Section 5.2 uses the general measure of war intensity to establish that the estimated elasticity reflects the maritime margin rather than the destruction of productive capacity that accompanied it.

2.3. The Relative Cost of Sea against Land Transport

As will be shown in Section 3, the reduced-form coefficient identifies the product $-\eta\kappa$, where κ maps the conflict index onto the log relative cost of sea against land transport.

⁴The national series in Panels A and B is not the sum of the oblast panel. Because the 10-kilometer buffers of nearby ports overlap, events are deduplicated across ports before national aggregation, so the country totals lie strictly below the port-level sum. The national PCA is also fitted on the post-invasion subsample only, since pre-war national counts are essentially zero. These series are descriptive and enter no estimation.

⁵For the port-proximate index we retain kinetic subtypes and infrastructure tags in ACLED, since the object of interest is damage to port facilities. For the general oblast-level war intensity, we use all the events described as political violence and strategic developments, since the object is wartime disruption to production more broadly.

Recovering the elasticity therefore requires an independent measure of how that relative cost moved after February 2022. This subsection constructs one from quarterly freight cost series for Ukraine’s three principal modes over 2019-2024, and uses it to estimate κ rather than to anchor it at a single point.

Data. The sea series is the ocean freight rate for the Odesa-Alexandria wheat route, in USD per metric tonne, from Table 9 of the USDA Agricultural Marketing Service *Ukraine Grain Transportation* report, with route-level data collected by the Center for Transport Strategies in Kyiv. The benchmark route uses handysize vessels of 25,000-30,000 metric tonne capacity. Road costs come from the truck cost index compiled jointly by the Center for Transport Strategies and Zernovoz, in USD per metric tonne per 100 miles. Rail costs come from the same USDA report and measure the cost of moving wheat by rail from central Ukraine to the export ports, in USD per metric tonne. They are calculated under the Ukrzaliznytsia tariff rules and include delivery to the station and the rental of a grain hopper wagon, but exclude wagon positioning, elevator and station fees, security and forwarding services. All series are aggregated to calendar quarters and rebased to 2021Q4 = 100.⁶

The relative cost measure divides the sea index by a weighted average of the road and rail indices,

$$\text{Ratio}_t = \frac{\text{Sea index}_t}{(1 - \omega_R) \text{Road index}_t + \omega_R \text{Rail index}_t}, \quad (1)$$

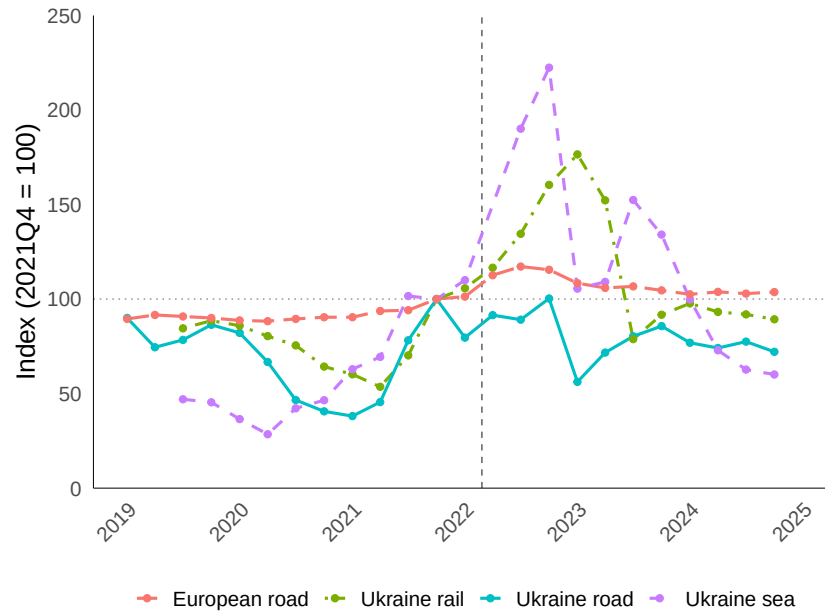
where $\omega_R = 0.328$ is the pre-war (2019-2021) rail share of overland export value in the estimation sample, consistent with rail accounting for about a tenth and road for one-fifth to one-quarter of export value before the invasion (Figure 1).

Figure 2 shows that the post-invasion shock to relative costs was driven mainly by sea freight. Sea freight from Ukraine rose to 190 index points in 2022Q3 and 222 in 2022Q4, fell back to 106 in 2023Q1 after the Black Sea Grain Initiative took effect, rose again to 152 in 2023Q3 after the Initiative lapsed, and declined to 60 by 2024Q4. Land costs moved far less. Road costs in USD fluctuated between 56 and 100 after the invasion and settled at 72-78 in 2024.⁷ Rail costs rose from 106 in 2022Q1 to 160 in 2022Q4 and

⁶Appendix D reports the validation exercises. The sea series is cross-checked against the IGC Grain Ocean Freight Index for the Black Sea region, which covers a broader basket of routes, and the Ukrainian road series against the *European Road Freight Rate Development Benchmark* published by Transport Intelligence, Upplly and the International Road Union, together with correlation and regression evidence that the benchmark sea rate tracks the aggregate movement in Black Sea freight costs.

⁷The decline in dollar road costs is consistent with the depreciation of the hryvnia, reported in

FIGURE 2. Ukraine and European transport cost indices



Sources: USDA AMS/CFTS Table 9 (Ukraine sea); CFTS/Zernovoz (Ukraine road); USDA AMS/CFTS (Ukraine rail); Ti/Upply/IRU *European Road Freight Rate Development Benchmark* (European road). All series rebased to 2021Q4 = 100. Quarterly averages.

Note: Rail data cover 2019Q3–2024Q4, sea data extend through 2024Q4. All Ukrainian series are in USD per metric tonne. Rail costs include wagon rental but exclude wagon positioning, elevator fees and forwarding services.

177 in 2023Q1, consistent with the higher cost of wagon rental, then fell to 79 in 2023Q3 and stayed between 89 and 98 in 2024. The weighted land composite ranged between 80 and 120 over 2022–2023, against 106–222 for sea, so the sea-to-land ratio largely tracks the sea series and peaks at 1.91 in 2023Q3. European road freight rose modestly, to 117 in 2022Q3, and stayed between 103 and 108 from 2023 onward, which locates the shock in Ukrainian freight specifically rather than in European logistics markets.⁸

Table 1 evaluates the ratio at windows corresponding to the approximate anniversaries of the invasion, each taken as the calendar quarter containing that date. The ratio rises to 1.83 at six months (2022Q3). The increase comes almost entirely from sea freight: road costs fell while rail costs rose, leaving the land composite roughly unchanged at 104. The ratio falls to 1.10 at one year, as sea freight eases under the Black Sea Grain Initiative while rail costs peak, edges up to 1.19 at two years, and reaches 0.77 by 2024Q4, at which point sea freight is cheaper than the land average in index terms. The reversal

Appendix A, Figure A.13.

⁸The trajectory is consistent with the assessments of Fernandes, Teixeira, and Santos (2023) and Espitia et al. (2025). See Appendix D for discussion.

TABLE 1. Ukraine sea freight index relative to land freight, selected quarters (2021Q4 = 100).

Window	Quarter	Sea	Road	Rail	Land avg	Ratio	Δ vs baseline
Baseline	2021Q4	100.0	100.0	100.0	100.0	1.00	0.00
3 months	2022Q2	—	91.5	116.6	99.7	—	—
6 months	2022Q3	190.1	89.1	134.5	104.0	1.83	0.83
1 year	2023Q1	105.5	56.2	176.5	95.7	1.10	0.10
2 years	2024Q1	99.8	76.9	97.7	83.7	1.19	0.19
3 years	2024Q4	60.1	72.1	89.3	77.7	0.77	-0.23

Sources: see Figure 2. Indices rebased to 2021Q4 = 100.

Δ vs baseline = ratio minus 1.00.

Sea index not available for 2022Q2 (Black Sea grain blockade). 2024Q4 is the latest available quarter (approximately 2 years and 10 months post-invasion).

is consistent with the recovery of Black Sea shipping under Ukraine’s unilateral corridor. The anniversary windows miss the highest values of the ratio, 1.85 in 2022Q4 and 1.91 in 2023Q3, when sea freight rose again after the Initiative lapsed while rail costs fell back.

No sea observation exists for 2022Q2. Ukraine’s Black Sea ports were closed or under threat from late February through most of that quarter, so no commercial rate was quoted for the benchmark route. The absence is itself a measure of the blockade’s severity rather than a gap in the data: the relative cost of sea transport in that quarter was effectively prohibitive, and 2022Q3 is the first quarter in which the corridor reopened sufficiently for rates to be quoted. The observed ratios therefore understate the relative shock at its most severe. Section 3.4 uses the quarterly series to estimate the mapping from the conflict index to relative transport costs.

3. Transport Mode Elasticity of Substitution: Empirical Strategy

3.1. Transport-Mode Choice

We start with a simple model of transport-mode choice, following Tolva (2026), that maps relative freight rates to relative mode-level trade flows. Importers in destination d purchase product i from Ukrainian origin region o in month t at a factory-gate (FOB) price p_{iodt} that is invariant to the mode of shipment. Delivery by mode $k \in \mathcal{K} = \{\text{Maritime, Railway, Automobile, Air, Other}\}$ entails an iceberg transport cost $\tau_{iodt}^k \geq 1$, so the delivered (CIF) price of a unit shipped by mode k is $\tau_{iodt}^k p_{iodt}$.

Shipments arriving by different modes are imperfect substitutes from the importer's perspective, as they differ in transit time, reliability, lot size, and handling requirements. Transit time in particular carries real costs, so rerouting through a slower mode raises the effective trade cost even when the freight rate is comparable (e.g., Hummels and Schaur 2013; Djankov, Freund, and Pham 2010). They are combined in a CES aggregate

$$Q_{iodt} = \left[\sum_{k \in \mathcal{K}} (Q_{iodt}^k)^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \quad \eta > 1, \quad (2)$$

where Q_{iodt}^k is the physical quantity shipped by mode k and η is the elasticity of substitution between transport modes. As in Tolva (2026), we restrict $\eta > 1$, so that modes are substitutes rather than complements.

Given (2) and mode-invariant factory-gate prices, the exact price index of the mode composite is

$$P_{iodt} = p_{iodt} T_{iodt}, \quad T_{iodt} \equiv \left[\sum_{k \in \mathcal{K}} (\tau_{iodt}^k)^{1-\eta} \right]^{\frac{1}{1-\eta}}. \quad (3)$$

Cost minimization over modes yields the mode demands and CIF expenditure shares

$$Q_{iodt}^k = \left(\tau_{iodt}^k / T_{iodt} \right)^{-\eta} Q_{iodt}, \quad \pi_{iodt}^k \equiv \frac{\tau_{iodt}^k p_{iodt} Q_{iodt}^k}{P_{iodt} Q_{iodt}} = \frac{(\tau_{iodt}^k)^{1-\eta}}{\sum_j (\tau_{iodt}^j)^{1-\eta}}. \quad (4)$$

Three consequences of $\eta > 1$ are used below. Relative quantities respond to relative costs with elasticity η , so $\eta > 1$ results in reallocation of expenditures away from a mode whose cost rises, and its CIF share falls. The index T_{iodt} rises when a mode becomes unavailable, so the loss of maritime access raises the composite cost of delivery. The composite (2) remains well defined when a mode is unused, as in the single-mode spell-months that dominate our sample. In the model, such a zero corresponds to the mode being unavailable ($\tau^k = \infty$).

Demand for the composite is standard: $Q_{iodt} = D_{iodt} (p_{iodt} T_{iodt})^{-\sigma}$, where D_{iodt} collects product-destination demand shifters and σ is the upper-tier (across-origin) demand elasticity. As shown below, neither D , p , T , nor σ appears in our estimating equation: all objects common to the two modes within a spell-month cancel in the relative outcome.

3.2. From the Model to Trade Data

Ukrainian trade data measure, for each export spell and month, the physical quantity Q_{iodt}^k and the FOB value $X_{iodt}^k \equiv p_{iodt} Q_{iodt}^k$ of shipments by mode. CIF expenditure at destination, $V_{iodt}^k \equiv \tau_{iodt}^k p_{iodt} Q_{iodt}^k$, is *not* observed, since the mirror data with a breakdown by modes is missing. These objects map differently into η . For any two modes m and l , equation (4) implies

$$\log(V_{iodt}^m / V_{iodt}^l) = \log(\tau_{iodt}^m / \tau_{iodt}^l) = (1 - \eta) \log(\tau_{iodt}^m / \tau_{iodt}^l). \quad (5)$$

$$\log(X_{iodt}^m / X_{iodt}^l) = -\eta \log(\tau_{iodt}^m / \tau_{iodt}^l), \quad (6)$$

$$\log(Q_{iodt}^m / Q_{iodt}^l) = -\eta \log(\tau_{iodt}^m / \tau_{iodt}^l), \quad (7)$$

The quantity and FOB-value mappings (6)-(7) coincide because the factory-gate price is mode-invariant and cancels from the ratio, leaving the same slope $-\eta$ ⁹. The attenuated slope $-(\eta - 1)$ in (5), which is negative because $\eta > 1$, arises only for CIF expenditures and shares as shown in Tolva (2026), since the increase in freight charges partly offsets the quantity reallocation. Since we work exclusively with export (FOB) data, our estimating equations are based on (6)-(7), and the estimated slope identifies $-\eta$ directly.

The land composite. Our empirical land aggregate sums railway and automobile flows, $Q_{iodt}^L \equiv Q_{iodt}^R + Q_{iodt}^A$ and $X_{iodt}^L \equiv X_{iodt}^R + X_{iodt}^A$. This arithmetic sum is exactly consistent with the model: substituting (4),

$$\frac{X_{iodt}^M}{X_{iodt}^L} = \frac{(\tau_{iodt}^M)^{-\eta}}{(\tau_{iodt}^R)^{-\eta} + (\tau_{iodt}^A)^{-\eta}} = \left(\tau_{iodt}^M / \tau_{iodt}^L \right)^{-\eta}, \quad (8)$$

$$\tau_{iodt}^L \equiv \left[(\tau_{iodt}^R)^{-\eta} + (\tau_{iodt}^A)^{-\eta} \right]^{-1/\eta},$$

so relations (6)-(7) hold exactly with the land cost index τ^L . Log-differentiating τ^L gives $d \log \tau^L = \omega^R d \log \tau^R + \omega^A d \log \tau^A$, where ω^k is mode k 's FOB-value share within the land composite. We set $\omega^R = 0.328$, the pre-war (2019-2021) rail share of overland export value in the estimation sample, so the change in the land cost index is, to first order, the

⁹Equations (7) and (6) coincide exactly only under mode-invariant factory-gate prices within a spell-month. If the product mix within an HS6 spell differs systematically across modes, unit values differ by mode and the two outcomes can diverge. Reporting results for both values and quantities serves as a specification check on the common-price assumption.

value-weighted average of the road and rail log cost changes. Note that τ^L is the cost aggregator for the FOB ratio rather than the CES price index of a land nest.

3.3. Blockade as a relative-cost shock

Mode-specific trade costs are not observed at the shipment level. As a first stage, we model the relative cost of maritime versus land transport using the instrument for military activity around the ports as

$$\log\left(\tau_{iodt}^M / \tau_{iodt}^L\right) = \alpha_{iod} + \alpha_{it} + \alpha_{ot} + \alpha_{dt} + \kappa (E_{iod} \times Z_{ot}) + u_{iodt}, \quad (9)$$

where α terms capture time-invariant spell-level relative costs (distance to ports, product handling characteristics), as well as product-, origin-, and destination-specific relative cost trends (fuel prices, congestion, seasonality), Z_{ot} is the blockade-intensity series for origin o , E_{iod} is the pre-war exposure of the spell to maritime transport, $\kappa > 0$ converts units of blockade intensity into log relative-cost changes, and u_{iodt} collects idiosyncratic relative-cost innovations. Mode-specific demand shocks (e.g., a destination-specific preference for containerized delivery) enter the relative demand symmetrically and can be folded into u_{iodt} without changing anything below.

Substituting (9) into (6) yields the estimating equation

$$\text{arsinh}(X_{iodt}^M) - \text{arsinh}(X_{iodt}^L) = \alpha_{iod} + \alpha_{it} + \alpha_{ot} + \alpha_{dt} - \eta \kappa (E_{iod} Z_{ot}) + \varepsilon_{iodt}, \quad (10)$$

$$\varepsilon_{iodt} \equiv -\eta u_{iodt},$$

where the fixed effects in (10) are rescaled versions of those in (9). The error term enters with the same structural multiplier $-\eta$ as the cost shock. Because the outcome is a within-spell ratio across modes, every determinant of the *level* of trade that is common to both modes—the factory-gate price p_{iodt} , the composite cost index T_{iodt} , total demand Q_{iodt} , and hence all demand shifters D_{iodt} and the upper-tier elasticity σ cancel exactly.

3.4. Estimating κ : From Conflict Events to Relative Costs

Equation (10) identifies the product $-\eta\kappa$, where κ is the slope mapping the conflict index onto the log relative cost of sea against land transport. The index is unit-free, so η is not recoverable without it. We estimate that slope rather than fixing it by normalization.

Let $\log\left(\tau_q^{sea} / \tau_q^{land}\right) = \ln(\text{Ratio}_q)$ denote the log sea-to-land cost ratio in quarter q , constructed in Section 2.3, and let $\bar{Z}_q^{\text{Odesa}}$ denote the Odesa oblast conflict index

averaged within the quarter.

The conflict index is zero by construction before February 2022, and the cost ratio is normalised to its last pre-invasion quarter, 2021Q4. We impose that the mapping passes through the origin, so that κ measures the change in log relative costs from that pre-invasion benchmark. We estimate

$$\log\left(\tau_q^{sea}/\tau_q^{land}\right) = \kappa \bar{Z}_q^{Odesa} + \varepsilon_q \quad (11)$$

over the eleven post-invasion quarters in which both series are observed. Table 2 reports the estimates and Figure A.7 the underlying scatter for column (1). The baseline index yields $\hat{\kappa} = 0.126$ with a standard error of 0.034, while the estimate ranges from 0.087 to 0.126 across buffer radii and source combinations¹⁰. Odesa is the natural reference oblast since it is the largest port oblast by pre-war throughput, and the benchmark freight rate is quoted on a route originating there. Each instrument variant and radius receives its own $\hat{\kappa}$, so the rescaling is internally consistent with the shift entering each specification.

In particular, we rescale oblast level instrument as

$$\tilde{Z}_{ot} = Z_{ot} \times \hat{\kappa}, \quad (12)$$

where $\hat{\kappa}$ is a respective coefficient in Table 2. Because the shift is rescaled before entering the regression, the obtained coefficients are directly implied elasticities of substitution, $\hat{\eta} = -\hat{\beta}$. Two standard errors are therefore relevant. The clustered errors reported in the estimation tables condition on $\hat{\kappa}$ and reflect only sampling variation in the trade data. Errors that additionally incorporate the uncertainty in $\hat{\kappa}$, computed by the delta method, are wider.

One of the limitations is that no sea rate is quoted for 2022Q2, when the benchmark route was closed, so the quarter in which the blockade was most binding contributes no observation to equation (11). If the true relative cost change in that quarter exceeded what the conflict index predicts, $\hat{\kappa}$ is too small and the implied elasticity correspondingly too large.

¹⁰The intercepts of the unrestricted regressions are insignificant throughout ($p \geq 0.19$; -0.098 with $p = 0.51$ for the baseline index), so the data do not reject the through-origin restriction.

TABLE 2. First Stage: Conflict Intensity and Relative Transport Costs

Dependent Variable:		$\log(\tau^{sea} / \tau^{land})$				
Index		PC1		PC2	PC3	PC4
Radius	10 km	5 km	2 km		10 km	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
$\bar{Z}_q^{Odesa}$	0.126*** (0.034)	0.113*** (0.031)	0.087*** (0.024)	0.108** (0.034)	0.117*** (0.037)	0.106** (0.037)
<i>Fit statistics</i>						
Observations	11	11	11	11	11	11
R ²	0.33708	0.33950	0.32676	0.21489	0.22663	0.14346

Note: Through-origin regressions of the log sea-to-land freight cost ratio on the Odesa oblast conflict index, averaged within quarter, over the eleven post-invasion quarters in which both series are observed (equation (11)). No sea rate is quoted for 2022Q2, when the benchmark route was closed. PC1 uses VIINA 2.0 only; PC2 adds ACLED, PC3 war-related fires, PC4 all three. R^2 is computed about the mean. Classical standard errors in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

3.5. Implementation

Functional form and zeros. Equation (10) is derived for the log ratio, undefined when either mode is unused in a given month, which is the case for the majority of spell-months in our data, since approximately 85% of spells use only one mode of transport, either vessel or land.¹¹ This precludes direct use of the log maritime-to-land ratio as the dependent variable.

Our primary implementation replaces the log ratio with the difference of inverse hyperbolic sine (IHS) transformations, $\text{arsinh}(X_{iodt}^M) - \text{arsinh}(X_{iodt}^L)$, which is a close proxy for $\log(X_{iodt}^M / X_{iodt}^L)$ when both flows are positive and non-trivial, while remaining defined at the corners¹². We further decompose the ratio into its components and estimate the maritime and land margins separately under IHS. A movement in the ratio can reflect contraction on one side, expansion on the other, or both, and reporting the two margins side by side makes the source and direction of the response transparent. We further estimate the level equations by Poisson pseudo-maximum likelihood, which accommodates zero outcomes naturally and is consistent under heteroskedasticity in the conditional mean (Santos Silva and Tenreyro 2006). Agreement between PPML and

¹¹Appendix Figures A.1 and A.2 provide detailed information on the distribution of the mode share in the sample.

¹²The discrepancy disappears for very large numbers, which holds for trade values expressed in US dollars or kilograms. See Chen and Roth (2024) for a discussion of potential caveats.

IHS estimates of the same margin suggests the result is not an artifact of the variance-stabilising transformation; a wedge between them typically signals that the response is concentrated at the extensive rather than the intensive margin.

3.6. Empirical Specifications

Event-study. We begin by documenting how the blockade affected the relative importance of sea versus overland transportation over time. The event study traces the dynamic response and allows us to assess pre-trends and anticipation effects. We estimate

$$\mu_{iodt} = \alpha_{iod} + \alpha_{it} + \alpha_{ot} + \alpha_{dt} + \sum_{\substack{h=\text{Jan19} \\ h \neq \psi}}^{\text{Sep25}} \beta^h E_{iod} \mathbb{1}\{t = h\} + \varepsilon_{iodt}, \quad (13)$$

where E_{iod} is pre-war maritime exposure, ψ is the reference period, and the fixed effects control for spell-specific characteristics (α_{iod}), product trends (α_{it}), origin trends (α_{ot}), and destination trends (α_{dt}). Standard errors are clustered at the destination-origin level.

Following Section 3.5, the outcome μ_{iodt} is constructed using the IHS difference, $\text{arsinh}(X_{iodt}^M) - \text{arsinh}(X_{iodt}^L)$ for values and $\text{arsinh}(Q_{iodt}^M) - \text{arsinh}(Q_{iodt}^L)$ for quantities. We additionally report results for mode-margins¹³

Difference-in-differences. The event study traces the full path of β^h but does not deliver a single structural parameter. For estimation we collapse the time dimension into the continuous blockade intensity, replacing the vector of period indicators with the rescaled shift of (12):

$$\mu_{iodt} = \alpha_{iod} + \alpha_{it} + \alpha_{ot} + \alpha_{dt} + \beta E_{iod} \times \tilde{Z}_{ot} + \varepsilon_{iodt}. \quad (14)$$

This is the empirical counterpart of (10), and under the normalization of Section 3.3 the coefficient recovers the implied elasticity directly, $\hat{\eta} = -\hat{\beta}$. The treatment varies across spells through pre-war maritime exposure E_{iod} and across origin-months through blockade intensity $\tilde{Z}_{ot}$ and identification comes from the interaction and not from the post-February 2022 level shift, which the period fixed effects absorb. $\tilde{Z}_{ot}$ is zero for all t

¹³We also report event studies for the individual margins, $\text{arsinh}(X_{iodt}^M)$, $\text{arsinh}(X_{iodt}^L)$, $\text{arsinh}(X_{iodt}^A)$ and $\text{arsinh}(X_{iodt}^R)$, and their quantity analogues, which decompose movements in the ratio into the maritime, land, automobile and railway components.

before February 2022, so the pre-invasion months serve as the untreated comparison for every spell regardless of its exposure. Regression model (14) imposes no restriction on pre-trends beyond those imposed by the fixed effects, while the event-study coefficients in Section 4 test that restriction directly. Moreover, because $\tilde{Z}_{ot}$ varies continuously after the invasion rather than switching on and remaining constant, $\hat{\beta}$ averages the response across the intensity distribution of the post-blockade period rather than estimating a single post-versus-pre contrast.

3.7. Identification threats

Equation (10) confines the threats to identification to mode-specific shocks at the spell-month level correlated with $E_{iod} \times \tilde{Z}_{ot}$ conditional on the fixed effects. We consider three candidates here. A fourth and more substantial concern that wartime disruption to production, rather than to maritime access, drives the measured reallocation requires evidence beyond the specification itself, and we address it separately in Section 5.2.

EU suspension of import duties and quotas. Our identification comes from the interaction of pre-war maritime exposure with blockade intensity, not from the post-February 2022 level shift alone, which the period fixed effects absorb. For the liberalization to bias the shift-share coefficient it would need to have differentially benefited products that were previously more maritime-dependent. Such a correlation is plausible, since the suspension applied largely to agricultural goods, which are among the most maritime-dependent categories in our sample (see Section 6 for details). Its direction, however, is unfavourable to a substitution interpretation only in the conservative sense: by making land routes to the EU more attractive for precisely these products, the liberalization would raise land shipments relative to maritime and inflate the measured elasticity. However, the fixed-effect structure (product-period, destination-period, origin-period) absorbs any common time trend in land-routed trade to EU destinations, so bias requires variation in the liberalization’s effect *within* product and *within* destination over time that also correlates with blockade intensity. And the estimates do not change materially when agricultural products are analysed separately (Section 5.2), for which the liberalisation was in force throughout.

Polish trucker blockades. The blockades began in November 2023 and continued into early 2024, constraining truck capacity on a key western corridor for part of our sample. Because they restricted the substitute mode rather than the disrupted one, they push

the maritime-to-land ratio up and attenuate our estimated elasticities. We control for destination-period fixed effects throughout. Extending the estimation window from July 2023, before the episode, to July 2024, which covers it in full, leaves the implied elasticity essentially unchanged, so the episode does not materially affect the headline estimate, which uses data through September 2025.

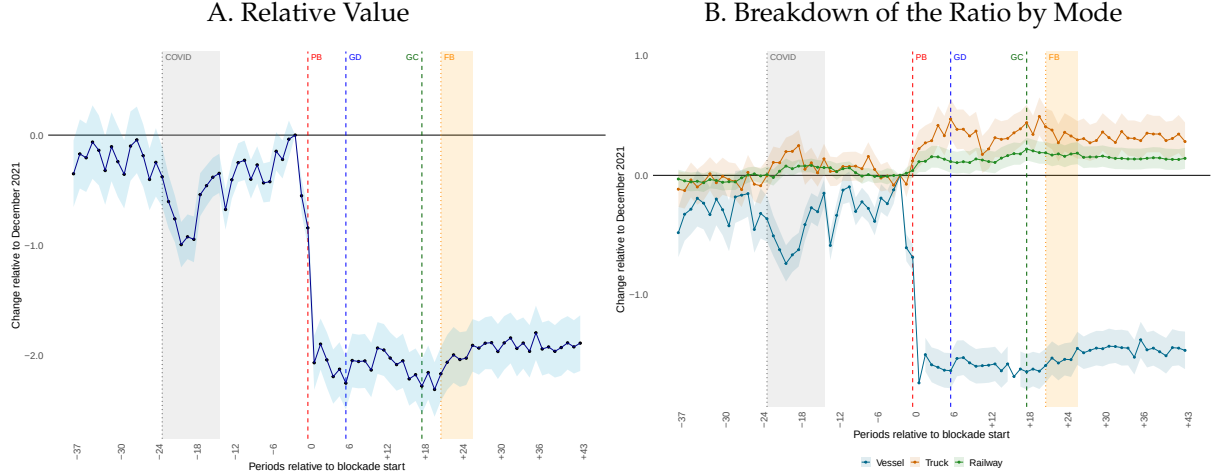
Definition of export origin. If the recorded origin reflects customs clearance rather than production location, pre-war export shares may misattribute port exposure to clearance hubs rather than to true dispatch regions. Provided clearance locations are sticky, this introduces classical attenuation bias, making our estimates a conservative lower bound. Endogenous rerouting of clearance away from port-adjacent oblasts after the blockade would be a more serious concern, since it would generate a spurious correlation between exposure and observed reallocation, but it is unlikely given the short-run costs of renegotiating established customs and logistics arrangements. Consistent with this, the leave-one-out exercise in Section 5.2 shows that no single origin oblast, including the Kyiv city acting as the dominant clearance hub, is pivotal to the estimate.

4. Patterns of Substitution among Transportation Modes

We begin with the general patterns of substitution between maritime and land transportation since the onset of the port blockade, which also allows us to examine the behavior of pre-trends. Figure 3 documents the evolution of maritime and overland trade flows using the event-study design of equation (13). Panel A plots the IHS difference between maritime and land export values, while Panel B decomposes the response by individual transport mode.

Each coefficient β^h is the interaction of a period indicator with pre-war maritime exposure E_{iod} , estimated under the same fixed-effect structure as our main specification (14). The plotted series therefore measures the differential path of exposed relative to unexposed spells, rather than the aggregate modal composition of Ukrainian exports, and the pre-blockade coefficients constitute a direct inspection of the parallel-trends. We use December 2021 as the reference period, the last month fully preceding any invasion-related anticipation. The reference period enters only (13), where a normalization is required to identify the period coefficients; the difference-in-differences specification (14) has no omitted category, since $\tilde{Z}_{ot}$ enters in levels and is zero for all months preceding February 2022. The estimated elasticity reported in Section 5 is therefore invariant to

FIGURE 3. Event Study: Maritime-to-Overland Value



Note: Coefficients β^h from equation (13), in which month indicators are interacted with pre-war maritime exposure E_{iodt} . Each coefficient measures the differential change of high- relative to low-exposure spells, relative to December 2021. Panel A: outcome $\text{arsinh}(X_{iodt}^M) - \text{arsinh}(X_{iodt}^L)$. Panel B: the same specification estimated separately for arsinh of vessel, truck and railway export values. The horizontal axis counts months relative to February 2022. Fixed effects and sample as in Table 3. Shaded bands are 95% confidence intervals; standard errors clustered by origin-destination pair. Vertical markers: COVID-19, March 2020; PB, port blockade, February 2022; GD, Black Sea Grain Initiative, July 2022; GC, Ukrainian unilateral corridor, August 2023; FB, Polish border blockade, November 2023-early 2024 (shaded).

this choice.

Panel A displays one substantial pre-blockade departure from the reference level. During the COVID-19 disruption of 2020, the differential ratio falls, driven by sailing cancellations, port congestion, and container shortages (USITC 2020; Mańkowska et al. 2021). The episode is transitory: the coefficients recover fully over the course of 2021 as global trade and shipping demand rebounded (Unctad 2021; Gu and Liu 2025), and from mid-2021 through December 2021 the series is flat and statistically indistinguishable from zero. Panel B shows the same pattern mode by mode, with vessel, truck, and railway coefficients tightly clustered around the reference level over the eighteen months preceding the invasion.

The COVID episode is informative rather than merely incidental. It confirms that maritime-exposed spells do respond differentially to global shipping shocks, as one would expect, and it establishes the form such responses take in our data: a displacement of bounded magnitude followed by full reversion within roughly a year. This is the relevant comparison for what follows. The break at the onset of the port blockade in February 2022 is of a different magnitude and a different character. The differential ratio drops sharply within two months and, unlike after COVID, does not revert to its pre-war level over the subsequent forty-three months, despite the partial recoveries

discussed below. This indicates a persistent shift in the modal composition of exports among maritime-dependent spells rather than a temporary disruption.

Panel B shows that the maritime decline was accompanied by increases in both truck and railway shipments, confirming that land routes absorbed part of the displaced maritime trade. The land response was far smaller than the maritime loss, however: the decline in vessel shipments of exposed spells is several times larger than the rise in truck and railway shipments, so total exports of exposed spells declined. The composition of the land response also evolved. Truck shipments rose immediately and by more than railway shipments throughout, with the gap widening as road logistics capacity expanded, while the railway response stayed comparatively flat. The limited expansion of rail anticipates the sectoral evidence in Section 6 and the policy discussion in Section 7, where rail capacity emerges as the binding constraint on substitution.

Three subsequent events produced partial reversals. The Black Sea Grain Initiative of July 2022 led to a modest recovery in vessel shipments, visible in Panel B, though the ratio remained well below its pre-war level. A more sustained recovery followed the opening of the Ukrainian unilateral grain corridor in August 2023, coinciding with a decline in truck and rail usage that is consistent with some trade switching back to maritime once corridor access was restored. The western border blockade by farmers and truckers in late 2023 and early 2024 introduced a further temporary disruption to overland flows, visible as a spike in the truck and rail series before reverting. None of these episodes returns the ratio to anything approaching its pre-blockade level.

The main findings are robust across alternative specifications. Figure A.5 re-estimates with January 2022 as the reference month. The comparison with Figure 3 shows a decline between December 2021 and January 2022, consistent with exporters beginning to shift away from maritime routes as the military threat became apparent. The movement is substantially smaller than the February 2022 break and, importantly, falls outside the 2019-2021 window used to construct pre-war exposure E_{iod} , so it cannot mechanically contaminate the exposure measure. Because $\tilde{Z}_{ot}$ is zero in January 2022, any such anticipation is treated as untreated variation in equation (14) and, if anything, attenuates the estimated elasticity. Figure A.6 replicates the analysis using export quantities rather than values, yielding the same pattern as Figure 3: a sharp and persistent decline in the differential maritime-to-overland ratio after February 2022, with truck shipments rising more than railway shipments throughout.

The event-study evidence supports the identifying assumption of the shift-share design, though the relevant claim requires care. It is not that exposed and non-exposed

spells never moved differentially before the blockade: the COVID episode shows that they did. The claim is that such movements were bounded and mean-reverting, and that no differential trajectory was under way at the onset of the blockade that could plausibly be mistaken for the treatment effect. The post-blockade break neither reverts nor resembles the COVID episode in shape or persistence. This reading is reinforced by the structure of the estimating equation. Because $\tilde{Z}_{ot}$ is identically zero before February 2022, the treatment variable $E_{iod} \times \tilde{Z}_{ot}$ takes the value zero for every spell in the pre-period regardless of exposure. Pre-blockade differential movements therefore enter the error term rather than the regressor and cannot mechanically bias $\hat{\beta}$. The pre-period contributes to estimation through the fixed-effect structure rather than as a control group in the conventional difference-in-differences sense. What the pre-period must establish is not the absence of differential movement but that no such movement persists into the post-blockade window in a form that tracks the intensity profile of $\tilde{Z}_{ot}$. The checks in Section 5.2, which control directly for general war intensity and restrict the instrument to oblasts never subject to ground combat, address that question directly.

5. Aggregate Estimates

In this section, we present the aggregate elasticity of substitution between maritime and overland transport, together with the sensitivity checks that bound it. Every specification includes product $\times$ origin $\times$ destination fixed effects, which hold constant the level of trade within a spell, and time-varying effects at the product, origin, and destination level, which absorb shifts in trade composition, regional production shocks, and destination-specific demand. Identification therefore comes from variation in port-proximate conflict across origins within a product and month, applied to spells that differed in their pre-war reliance on maritime transport. Standard errors are clustered by origin $\times$ destination throughout.

5.1. Baseline Estimates

Baseline estimate using FOB values. We begin with outlining the baseline result. We estimate equation (14) on FOB values, using a binary indicator of pre-war vessel use as the exposure share and the first principal component of conflict events within 10 km of Ukrainian ports as the shift. The shift is scaled by $\hat{\kappa}$, the first-stage slope estimated in Section 3.4, so the regressor is expressed in log relative cost units and the coefficient on the IHS difference is directly the negative of the elasticity.

Table 3 reports the result. The coefficient on the differenced inverse hyperbolic sine outcome is $\hat{\beta} = -2.254$, implying an elasticity of substitution of $\eta = 2.25$. Spells more exposed to the blockade reallocated away from maritime toward overland transport. The two margins estimated separately show why: vessel trade contracted sharply (-1.83 in column 2) while overland trade rose modestly ($+0.42$ in column 3). Overland routes absorbed part of the maritime disruption rather than replacing it.

TABLE 3. Baseline Results for the Implied Elasticity of Maritime–Land Substitution

Dependent Variables: Model:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$ (1) OLS	$\text{arsinh}(X_{iod}^M)$ (2) OLS	$\text{arsinh}(X_{iod}^L)$ (3) OLS	X_{iod}^M (4) Poisson	X_{iod}^L (5) Poisson
<i>Variables</i>					
$E_{iod} \times Z_{ot}$	-2.254*** (0.313)	-1.834*** (0.139)	0.420* (0.229)	-1.121* (0.572)	0.305 (0.261)
<i>Fixed-effects</i>					
Product×Destination×Origin	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓
<i>Fit statistics</i>					
Observations	5,939,649	5,939,649	5,939,649	1,400,041	4,261,327
R ²	0.48209	0.36922	0.50675	0.84241	0.86957

Note: All specifications follow equation (14) and include product×destination×origin, product×period, destination×period, and origin×period fixed effects. Z_{ot} is the first principal component of VIINA 2.0 conflict events within a 10 km radius of Ukrainian ports, scaled by $\hat{\kappa}$, the estimated slope of the log relative maritime-to-overland freight cost on the Odesa conflict index (Section 3.4); the coefficient is therefore an elasticity. E_{iod} is a pre-war (2019–2021) indicator for vessel use within a product–destination–origin spell. Column (1) reports the IHS difference between vessel and land value; columns (2) and (3) the two margins separately; columns (4) and (5) the same margins by PPML. Columns (4) and (5) retain fewer observations because Poisson estimation drops fixed-effect groups whose outcome is zero throughout; the two margins are estimated on different samples and their difference has no structural interpretation. Standard errors clustered by destination×origin in parentheses and conditional on $\hat{\kappa}$. Sample: January 2019–September 2025. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

The PPML specifications in columns (4) and (5) corroborate the decomposition under a different functional form. The vessel-side contraction survives (-1.12 , significant at the 10 per cent level), while the land coefficient is positive but statistically indistinguishable from zero ($+0.31$). The contrast between a positive IHS land coefficient and an insignificant PPML one suggests that the overland response was concentrated among smaller flows rather than in the large shipments that dominate aggregate overland value, consistent with substitution operating through new and reactivated trading relationships more than through the expansion of the largest pre-existing overland flows.

Two standard errors are relevant to inference on η . Those reported in Table 3 are clustered by destination×origin and condition on $\hat{\kappa}$. Carrying the first-stage uncertainty through by the delta method widens the standard error from 0.31 to 0.69. The one-sided

hypothesis $\eta \leq 1$ is rejected at the 5 per cent level ($p = 0.034$), confirming that maritime and overland transport are substitutes rather than complements.

The remainder of this subsection asks whether the conclusion depends on the discretionary choices embedded in the baseline. Tables 4 and A4 report the differenced IHS specification across seven alternatives for values and quantities, varying the construction of the exposure measure, the radius used to aggregate conflict events, the conflict data sources entering the index, and the destination sample. Tables A1-A3 provide the baseline for quantities and for single-mode shipments.

TABLE 4. Aggregate Implied Elasticity under Different Specifications

Dependent Variables:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$							
Model:	Baseline	Cont. expo.	5 km	2 km	PC2	PC3	PC4	Excl. RU, BY
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
$E_{iod} \times \tilde{Z}_{ot}$	-2.254*** (0.313)	-3.032*** (0.343)	-2.507*** (0.372)	-2.634*** (0.553)	-3.368*** (0.464)	-2.815*** (0.372)	-3.648*** (0.486)	-2.457*** (0.342)
<i>Fixed-effects</i>								
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>								
Observations	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,296,347
R ²	0.48209	0.48222	0.48211	0.48206	0.48223	0.48216	0.48227	0.48580

Note: All columns estimate equation (14) on export values with wide definition of modes and the baseline fixed effects; the outcome is $\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$. Column (1) is the baseline: binary pre-war vessel exposure and PC1 of VIINA 2.0 events within 10 km of ports. Each remaining column changes one element. Column (2) replaces the binary exposure with the pre-war vessel share of spell export value. Columns (3)-(4) count conflict events within 5 and 2 km of ports. Columns (5)-(7) use alternative indices: PC2 adds ACLED events, PC3 adds war-related fires, and PC4 adds all three sources. Column (8) excludes exports to Russia and Belarus. Each index is scaled by its own $\hat{\kappa}$ (Section 3.4), so the coefficients equal $-\hat{\eta}$. Standard errors clustered by destination×origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

Quantities and values. The quantity estimate implies an elasticity of 2.36, against 2.25 for values, a difference well within one standard error. Because FOB value is the product of unit value and physical volume, a value estimate materially exceeding its quantity counterpart would indicate that part of the measured response operated through repricing rather than through the reallocation of shipments across modes. The near-equality rules this out. The response appears in physical volumes, which is what the structural interpretation requires.

Multimodality. The narrow mode definition retains only purely vessel- or purely land-routed flows and drops shipments with mixed sea-land legs (Table A14). Under it, the

elasticity falls modestly, to 2.00 for values and 2.03 for quantities, and the one-sided test still rejects $\eta \leq 1$ at the 5 per cent level once the uncertainty in $\hat{\kappa}$ is included ($p = 0.049$ and 0.046). The distance results in Tables A5 and A6 sharpen the interpretation: the response is strongest at intermediate distances of 1,500-3,000 km, with elasticities of 4.10 for values and 3.91 for quantities, and it is there that both margins move most, with the largest maritime decline and the only large overland increase. This is the range over which multimodal itineraries are viable: close enough for an overland leg to be feasible, far enough that a purely overland route would not have been chosen in the first place. At shorter distances little exists to reallocate, and the elasticity (1.18 for values) cannot be distinguished from one. At the longest distances the elasticity remains significant (2.51), but it reflects mainly the contraction of maritime trade, as the overland margin barely responds. So, the blockade activated rerouting where the transport network made it available.

Continuous exposure. Replacing the binary indicator with the continuous pre-war maritime share raises the elasticity to 3.03 for values (column 2 of Table 4) and 3.22 for quantities (Table A4). This reflects a different maintained assumption rather than a robustness failure. The continuous measure imposes proportionality between pre-war maritime dependence and the effective log relative-cost shock. It also weights the sample toward relationships in which maritime trade was largest, so the instrument bites harder. We retain the binary specification as the baseline because it requires the weaker assumption and delivers the more conservative value.

Buffer radius. Narrowing the buffer used to aggregate conflict events raises the elasticity: 2.51 at 5 km and 2.63 at 2 km for values, against 2.25 at 10 km, with quantities following the same pattern (2.63 and 2.81 against 2.36). Part of this movement is mechanical. The first stage in Table 2 shows that $\hat{\kappa}$ also falls as the buffer narrows, from 0.126 at 10 km to 0.113 at 5 km and 0.087 at 2 km, and since η is recovered from a shift scaled by $\hat{\kappa}$, a smaller scaling factor inflates the implied elasticity for a given underlying response. The tighter buffers therefore do not provide independent evidence that strikes closest to the quay matter most. What they establish is that the conclusion does not depend on the buffer choice. We retain 10 km as the baseline because it corresponds to the spatial scale over which strikes plausibly disrupt port operations, and because it yields the most conservative of the three estimates.

Sources of conflict data. The baseline shift is built from VIINA 2.0 alone, so a natural question is whether the result depends on that source. Columns (5)-(7) of Table 4 re-estimates using three alternative indices, each built by the same principal-component procedure and each with its own estimated $\hat{\kappa}$: VIINA 2.0 together with ACLED military and infrastructure events (PC2), VIINA 2.0 together with the *Economist* war-fires series (PC3), and all three sources combined (PC4). The alternatives are informative in different ways. ACLED overlaps with VIINA in underlying source material but is human-coded rather than machine-classified. The war-fires series derives from satellite thermal anomalies rather than news reporting, so agreement with it cannot reflect correlated media coverage.

The value elasticity is 2.25 in the baseline, 3.37 under PC2, 2.82 under PC3, and 3.65 under PC4, with quantity estimates close to their value counterparts throughout (2.36, 3.52, 2.93 and 3.80). With the uncertainty in $\hat{\kappa}$ included, all four reject $\eta \leq 1$ at the 5 per cent level. The alternative indices yield larger point estimates, so the VIINA-only baseline is the most conservative of the four, and the differences are within one standard error once the uncertainty in $\hat{\kappa}$ is taken into account, and the spread is within the range traced by the other sensitivity checks. Since satellite thermal detection and news-based event coding share no measurement technology, the agreement between PC1 and PC3 rules out correlated error in media reporting of strikes near ports as an explanation for the result. We return in Section 5.2 to the question of what the ACLED component adds, where general conflict intensity is controlled for directly.

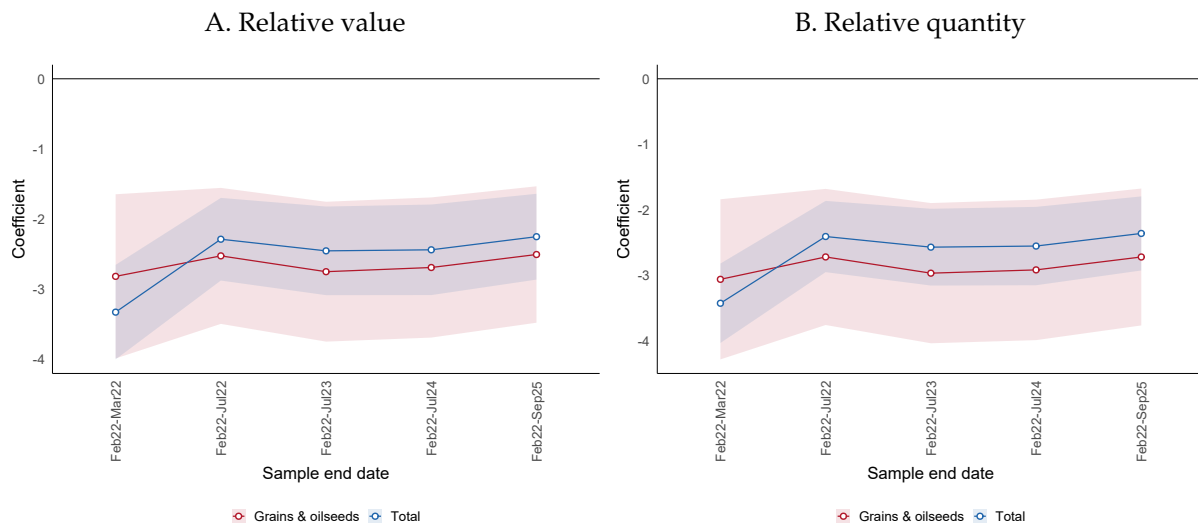
Excluding Russia and Belarus. Column (8) of Tables 4 and A4 drops all observations involving Russian or Belarusian destinations, trade with whom ceased at the onset of the full-scale invasion. The implied elasticity rises slightly, to 2.46 for both values and quantities, against 2.25 and 2.36 in the baseline, and the one-sided test rejects $\eta \leq 1$ at the 5 per cent level once the uncertainty in $\hat{\kappa}$ is included ($p = 0.026$ and 0.024). The small increase is consistent with the collapse of predominantly overland trade with these two neighbours slightly attenuating the baseline. The estimated substitution therefore reflects a broad rerouting response across the export network rather than the disruption of specific trade relationships.

Short and long horizons. Figure 4 traces the elasticity across estimation windows. The short-run estimates are the largest, at 3.33 for values and 3.43 for quantities over February-March 2022, the first two months of the blockade. They decline as maritime

access was partially restored: to 2.29 and 2.41 once the window extends to July 2022, stay broadly stable at 2.4-2.6 through windows ending in July 2023 and July 2024, and settle at 2.25 and 2.36 over the full window. Grains and oilseeds, the categories most reliant on Black Sea ports before the invasion, follow a flatter path: their implied elasticity is below the aggregate in the first two months (2.82 for values) but stays between 2.5 and 2.8 thereafter, above the aggregate in every later window.

Figure A.8 decomposes the value estimates by mode and shows why the two paths differ. The maritime coefficient (Panel A) falls sharply in both samples, and for grains and oilseeds it recovers by more over longer windows, consistent with partially regained access through the successive corridor arrangements. At the same time, the overland coefficient for grains and oilseeds (Panel B) grows over time, driven by trucking (Panel C), identifying road crossings into the European Union as the primary margin of adjustment for these goods, although the grain-specific estimates are imprecise. For the aggregate, the overland response is smaller and stable. The railway coefficient (Panel D) is small throughout being the largest in the first two months and declines thereafter, consistent with rail absorbing the initial shock before road capacity expanded. The blockade induced a large and persistent modal shift in the aggregate, while for agricultural commodities partial maritime recovery and expanding road exports offset each other in the relative outcome.

FIGURE 4. Short- and Long-Run Elasticities of Substitution



Note: Coefficients on $E_{iod} \times \tilde{Z}_{ot}$ from equation (14) with the baseline fixed effects, estimated on samples starting in January 2019 and ending at the indicated month; each coefficient equals $-\hat{\eta}$. Panel A: outcome $\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$ (values). Panel B: $\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$ (quantities). *Total* uses all products; *Grains & oilseeds* restricts the sample to HS chapters 10 and 12. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by κ . Shaded bands are 95% confidence intervals based on standard errors clustered by destination $\times$ origin.

5.2. Disentangling Transport Disruption from Production Disruption

The blockade did not arrive alone. The campaign that closed the ports also destroyed productive capacity, displaced workers, and cut power. If the estimated coefficient reflects that destruction rather than reallocation across modes, the structural interpretation fails. The fixed effects in equation (14) absorb any shock common to an origin in a given month, but not one that affects maritime-exposed spells within that origin differently, which is the variation that identifies the coefficient. This subsection removes or absorbs, one at a time, each channel through which production disruption could masquerade as modal substitution.

Production disruption and modal substitution have different signatures. Destruction of capacity lowers shipments by both modes, whereas substitution lowers maritime and raises overland shipments. As a result, a falling maritime-to-land ratio is informative only if it is not driven by maritime losses alone. The checks below address this in two ways: by removing the sectors and regions where production losses were concentrated, and by absorbing or controlling for production shocks directly.

Narrow origin-sector cells. The baseline origin $\times$ period fixed effects absorb any shock common to all products from an oblast in a given month, but not shocks specific to a sector within that oblast, such as the destruction of a steel plant or a grain terminal. If such sector-specific shocks are correlated with maritime exposure, they could be misattributed to modal substitution. We therefore replace origin $\times$ period with origin $\times$ HS chapter $\times$ period fixed effects, restricting identification to comparisons within the same two-digit chapter, origin, and month, which makes it the most demanding specification in the paper. The implied elasticity *rises* relative to the baseline, to 2.87 for values and 2.94 for quantities (Table A7). The result does not depend on pooling across dissimilar product groups within an oblast, and the baseline is the more conservative of the two.

Sectors whose capacity was destroyed. The aggregate estimate could be driven by sectors that lost production capacity rather than maritime access. Metallurgy is the natural test case as KSE Institute (2025) records it as the sector with the heaviest capacity destruction, including the loss of the Illich and Azovstal works in Mariupol and repeated disruption at Zaporizhstal, and it accounted for a substantial share of seaborne exports. It is precisely where production and transport shocks are most likely to be confounded.

Table A8 re-estimates excluding all metallurgy spells (HS 72-83), around 11 percent

of the sample. Under the wide definition of modes the implied elasticity falls modestly, from 2.25 to 1.97 for values and from 2.36 to 2.07 for quantities, and both remain statistically above unity at the 10 per cent level once the first-stage uncertainty is taken into account. Were production destruction driving the result, dropping the sector in which it was most severe should have attenuated it substantially. It does not, indicating that the headline estimate reflects a pattern holding across the broader export basket rather than metallurgy's outsized war shock.

Under the narrow definition of modes, which retains only single-mode customs declarations (Table A14), the same exclusion lowers the implied elasticity to 1.25 for values and 1.21 for quantities, no longer distinguishable from unity while accounting for the first stage uncertainty. The narrow estimate thus relies substantially on base metals. For base metals, where production losses were most severe, we cannot separate modal substitution from production loss, and we place more weight on the wide-mode results, which are largely robust to the exclusion. The narrow-mode sensitivity in the checks that follow should be read in the same light.

Origins away from the front line. Proximity to combat could drive mode substitution through infrastructure damage or security restrictions rather than through the relative cost shock the instrument is designed to capture. Table A9 restricts the sample to oblasts away from the front line, and additionally reports results omitting Kyiv city, Ukraine's dominant logistics hub.¹⁴ Under the wide definition of modes the elasticity is 2.39 for values and 2.48 for quantities, close to the baseline, while omitting Kyiv city lowers it to 2.10 and 2.16. Hence, no single dominant origin directly affected by the war is responsible for the pattern.

Table A10 drops each origin oblast in turn. Across all 25 exclusions the value elasticity ranges from 2.08, excluding Zaporizhzhia, to 3.40, excluding Odesa, with quantities spanning a comparable 2.19 to 3.47. The estimate is most sensitive to the exclusion of the two main port oblasts, Odesa and Mykolaiv, and dropping either raises rather than lowers it. This implies that the identifying variation is not concentrated in the regions most exposed to the blockade.

Pre-war stocks and harvest timing. For grains and oilseeds (HS 10, 11, 12, 23), exports in the months immediately after the invasion were drawn from the 2021 harvest already

¹⁴The restricted sample excludes Donetsk, Luhansk, Zaporizhzhia, Kherson, Kharkiv, Sumy, Chernihiv, Mykolaiv, and Kyiv oblast. Kyiv city is omitted only in the additional specification.

in storage, so contemporaneous production destruction cannot explain the substitution observed in that window. A distinct concern runs the other way: harvest timing and storage capacity may drive shipment timing independently of the transport cost shock, and differently from other sectors.

Tables A11 and A12 compare three windows: short run (February-March 2022), storage (February-June 2022, before the 2022 harvest) and full window (February 2022-September 2025). The comparison is made across the full sample and an agri-food subsample of roughly 8 per cent of observations. Both samples show larger short-run estimates, but the agri-food profile is flatter: its implied elasticity starts lower (2.62 for values, against 3.33 for all products) and declines by less, which is consistent with harvest and storage considerations smoothing shipment timing. In the full window the agri-food estimates of 2.32 for values and 2.54 for quantities sit close to the all-product figures of 2.25 and 2.36. Harvest dynamics generate transitory variation in short-run agri-food estimates but do not bias the long-run identification behind the headline result.

General conflict intensity. The identifying variation could reflect general wartime destruction correlated with, rather than distinct from, strikes on port infrastructure. Table A13 augments the baseline with two oblast-wide measures of conflict intensity, each interacted with pre-war exposure: ACLED event counts and the *Economist*/NASA FIRMS war-fires index, each scaled by its post-invasion standard deviation. Unlike the port-blockade index, both count events across the entire origin oblast rather than near ports. Both enter negatively and significantly, indicating that general conflict intensity independently suppresses maritime relative to overland activity.

The elasticity under the wide definition of modes falls from 2.25 to 1.91 for values and from 2.36 to 2.02 for quantities, while under the narrow definition of modes the estimates fall to 1.52 and are no longer distinguishable from one when accounting for the first-stage uncertainty. The attenuation may reflect correlation between the controls and the port blockade proxy since the same military campaign generates both, so a lower elasticity estimate may reflect the controls absorbing variation that belongs to the blockade itself. At the same time, this is the most comprehensive control for general war intensity in the paper.

Taken together, these checks bound the scope for production-side contamination. Under the wide mode definition the estimate survives absorbing sector-specific shocks within origin and period, excluding the sector whose capacity was most heavily de-

stroyed, restricting the sample to oblasts distant from the front line, dropping each origin in turn, isolating a window in which exports came from pre-war stocks, and controlling directly for general war intensity. Each removes a different component of wartime production disruption, and none removes the substitution response: the implied elasticity ranges from 1.91 to 2.87 across these checks and remains above one once the first-stage uncertainty is taken into account, at the 10 per cent level or higher. The departures move in economically interpretable directions rather than randomly. The narrow mode definition is more fragile: excluding base metals or controlling for general war intensity leaves it indistinguishable from one. We read the estimated reallocation as reflecting the disruption of maritime access rather than production losses correlated with pre-war maritime dependence, while acknowledging that these checks bound rather than eliminate residual contamination, particularly for base metals.

5.3. Synthesis across Specifications

Table 5 collects the estimates from the preceding subsections in one place, so that the range is visible at once rather than reconstructed from separate tables.

Panel A varies methodological choices that do not bear on identification: the buffer radius, the sources entering the conflict index, the treatment of compound intermodal declarations, and the choice between value and quantity outcomes. Across these the implied elasticity lies between 2.00 and 3.65 for values and between 2.03 and 3.80 for quantities. The most inclusive conflict index, PC4, gives the largest value, while retaining only single-mode declarations gives the smallest. Our baseline sits near the lower end, and value and quantity estimates agree closely throughout, which argues against repricing as the driver of the measured response.

Panel B varies the sample and the specification to separate maritime disruption from general wartime destruction correlated with pre-war port exposure. The spread is narrower, between 1.91 and 2.87 for values, and the lower bound is the general-conflict specification discussed above. Panel C splits destinations by distance. The response is strongest in the middle band, where an overland alternative existed but was not already dominant, and weakest at short range, where it was. Panel D varies the estimation window and sample composition. The response is stronger in the short run, so the baseline, estimated over the full period, is the more conservative reading. Panel E replaces the binary exposure indicator with the continuous pre-war maritime share, raising the implied elasticity to 3.03. As set out above, this is a different maintained assumption rather than a robustness failure, and we retain the binary specification for

TABLE 5. Synthesis of Aggregate Estimates

	Value	Quantity
Baseline (PC1, 10 km, binary exposure, wide modes)	2.254	2.363
<i>Panel A. Specification choices</i>		
Event radius: 5 km	2.507	2.631
Event radius: 2 km	2.634	2.806
Narrow mode definition	1.999	2.027
Instrument PC2 (VIINA + ACLED)	3.368	3.517
Instrument PC3 (VIINA + fires)	2.815	2.933
Instrument PC4 (all three sources)	3.648	3.796
<i>Panel B. Separating transport from production disruption</i>		
Origin $\times$ HS chapter $\times$ period FE	2.873	2.943
Excluding metallurgy (HS 72–83)	1.972	2.073
Origins away from the front line	2.391	2.483
Controlling for general war intensity	1.910	2.018
Excluding Russia and Belarus	2.457	2.456
<i>Panel C. Where an overland alternative exists</i>		
Destinations within 1,500 km	1.179	1.362
Destinations 1,500–3,000 km	4.101	3.913
Destinations beyond 3,000 km	2.515	2.259
<i>Panel D. Sample window and composition</i>		
Acute blockade only (to March 2022)	3.331	3.430
Through July 2023	2.457	2.573
Grains and oilseeds only	2.509	2.723
<i>Panel E. Alternative exposure assumption</i>		
Continuous pre-war maritime share	3.032	3.222
Leave-one-out across 25 oblasts (range)	2.082–3.399	2.189–3.469

Note: All entries report implied elasticities $\hat{\eta}$ from the differenced IHS specification, equation (14), with FOB values in the first column and physical quantities in the second. Unless stated otherwise, specifications use wide definition of modes, binary pre-war maritime exposure, and the baseline port-blockade index (PC1 of VIINA 2.0 events within 10 km of ports), each index scaled by its own $\hat{\kappa}$ (Section 3.4). Panel A varies methodological choices that do not bear on identification; the narrow mode definition retains only single-mode customs declarations. Panel B varies the sample and specification to separate maritime disruption from correlated production disruption (Section 5.2). Panel C splits destinations by distance from Ukraine. Panel D varies the estimation window and sample composition; grains and oilseeds are HS chapters 10 and 12. Panel E replaces the binary exposure indicator with the continuous pre-war maritime share, which additionally assumes that the relative-cost shock is proportional to pre-war maritime dependence. Underlying standard errors are clustered by destination $\times$ origin and conditional on $\hat{\kappa}$.

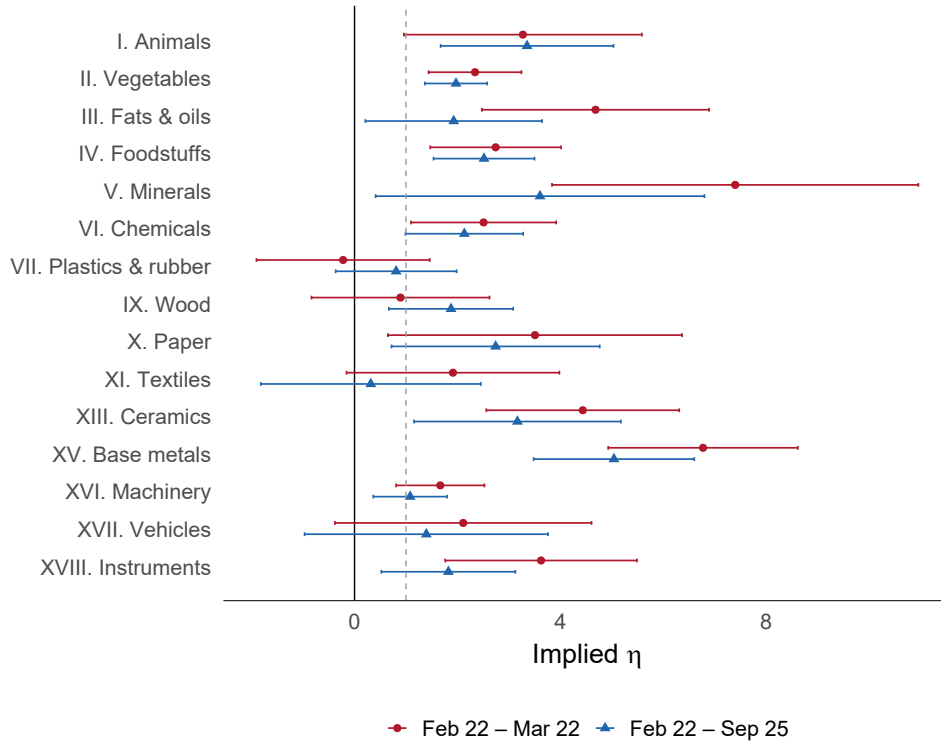
the weaker assumption it requires.

Read together, the table supports 2.25 as representative of the underlying elasticity rather than as an artefact of any single discretionary choice. The departures are neither large nor random: they move in directions that follow from what each variation does to the identifying variation, and stay within roughly 1.9 to 3.7. We use 2.25 as the reference value.

6. Sectoral Estimates

In addition to the average elasticity of substitution between transportation modes, we study its sectoral heterogeneity. We split the sample and apply specification (14) to each HS section separately, estimating both short-run (February–March 2022) and full-window (February 2022–September 2025) elasticities. Table 6 reports the estimates alongside two measures of pre-war maritime dependence, and Figure 5 plots them for sections with a pre-war vessel share of at least 5 percent.

FIGURE 5. Sectoral Short-Run and Long-Run Responses by HS Sections



Note: Implied elasticities $\hat{\eta} = -\hat{\beta}$ from equation (14), estimated separately for each HS section on export values with the baseline fixed effects, exposure and port-blockade index (PC1, 10 km, scaled by $\hat{\kappa}$). The outcome is $\text{arsinh}(X_{lod}^M) - \text{arsinh}(X_{lod}^L)$. Circles: samples ending in March 2022 (short run); triangles: samples ending in September 2025 (full window); all samples start in January 2019. Horizontal bars are 95% confidence intervals based on standard errors clustered by destination $\times$ origin and conditional on $\hat{\kappa}$. The dashed line marks $\eta = 1$. Sections with a pre-war vessel share of export value below 5% (Hides & skins, Footwear, Precious stones, Miscellaneous manufacturing) are omitted. Table 6 reports all sections

The response attenuates between short and long run. In fourteen of the nineteen sections the full-window elasticity lies below the short-run estimate, in several cases substantially: fats and oils falls from 4.68 to 1.93, minerals from 7.40 to 3.61, and base metals from 6.77 to 5.04. This mirrors the aggregate timing profile and is consistent with substitution operating as an emergency response that partially unwound as corridor

arrangements restored maritime access. The reversal was not monotone, since the Black Sea Grain Initiative of July 2022 was abandoned in July 2023 and overland flows were subsequently constrained by bottlenecks at the western borders, so the full window captures a sequence of shocks rather than a clean post-shock equilibrium.

The relationship with pre-war maritime dependence is non-monotone, and the peak lies in the middle of the distribution. The two most sea-dependent sections, vegetables and fats and oils, ship 94 and 92 per cent of pre-war value by vessel and return full-window elasticities of 1.97 and 1.93. The largest estimates come from sections in the intermediate range: base metals at a 0.72 vessel share yields 5.04, minerals at 0.65 yields 3.61, and animal products at 0.61 yields 3.35. Among sections with low pre-war vessel shares the picture is mixed. Plastics, textiles and vehicles return small and statistically insignificant estimates, while paper, ceramics and instruments show sizeable responses. For bulk agricultural commodities that shipped almost exclusively by sea, overland routes could absorb only part of the volume at comparable cost, so high maritime dependence limits rather than enables substitution, although their elasticities remain clearly above one. Sections that were already overland had little to reallocate. Substitution is largest where both modes were genuinely available before the war. This is the sectoral counterpart of the distance result in Panel C of Table 5: reallocation occurs where an alternative exists. The base-metal estimate should nevertheless be read with the caution set out in Section 5.2, since production losses in that sector were severe.

The estimates for sections with negligible pre-war maritime exposure should not be read as elasticities of substitution. Precious stones shipped essentially nothing by vessel before the war, and only one per cent of its exports are exposed, yet returns a full-window coefficient of 26.14 with a standard error of 8.26. There is no maritime margin from which to substitute, and whatever the coefficient reflects, it is not modal reallocation. The same caution applies to hides and skins, footwear, and miscellaneous manufacturing, which are marked in the table. Plastics and rubber returns a small negative short-run point estimate, -0.22 with a standard error of 0.86, which is a null rather than a sign reversal.

Figures A.9 and A.10 decompose the maritime-land ratio into its two margins, and Figures A.11 and A.12 further split the land composite into road and rail. Substitution is driven throughout by the contraction in maritime shipments, but which overland mode absorbed the displaced volume varies by sector: road carried the response for agricultural and food products (animals, vegetables, foodstuffs), whereas rail carried it for bulk industrial goods (minerals, ceramics, base metals).

TABLE 6. Sectoral Exposures and Implied Elasticities by HS Sections

HS Section	Vessel value	Exposed spells	Short run	Full window
I. Animals	0.61	0.67	3.272 (1.180)	3.353 (0.857)
II. Vegetables	0.94	0.58	2.342 (0.460)	1.972 (0.309)
III. Fats & oils	0.92	0.66	4.684 (1.126)	1.928 (0.876)
IV. Foodstuffs	0.59	0.51	2.743 (0.649)	2.517 (0.501)
V. Minerals	0.65	0.41	7.398 (1.816)	3.605 (1.630)
VI. Chemicals	0.28	0.30	2.509 (0.719)	2.134 (0.583)
VII. Plastics & rubber	0.15	0.24	-0.222 (0.859)	0.808 (0.600)
VIII. Hides & skins [†]	0.01	0.12	0.743 (2.780)	5.382 (1.996)
IX. Wood	0.20	0.28	0.893 (0.883)	1.875 (0.616)
X. Paper	0.15	0.23	3.507 (1.458)	2.742 (1.033)
XI. Textiles	0.07	0.06	1.913 (1.055)	0.316 (1.091)
XII. Footwear [†]	0.01	0.14	1.529 (1.980)	0.246 (1.907)
XIII. Ceramics	0.06	0.21	4.436 (0.956)	3.166 (1.026)
XIV. (Semi-)Precious stones [†]	0.00	0.01	19.104 (8.088)	26.140 (8.264)
XV. Base metals	0.72	0.33	6.773 (0.940)	5.042 (0.796)
XVI. Machinery	0.09	0.21	1.667 (0.438)	1.081 (0.366)
XVII. Vehicles	0.25	0.23	2.112 (1.272)	1.396 (1.207)
XVIII. Instruments	0.12	0.11	3.625 (0.951)	1.824 (0.665)
XX. Misc manufacturing [†]	0.03	0.19	1.646 (1.101)	0.933 (0.825)

Note: Implied elasticities $\hat{\eta} = -\hat{\beta}$ from equation (14), estimated separately for each HS section on export values with the baseline fixed effects, exposure and port-blockade index (PC1, 10 km, scaled by $\hat{\kappa}$). *Vessel value*: pre-war (2019-2021) vessel share of the section's combined maritime and overland export value. *Exposed spells*: share of the section's spells with any pre-war vessel shipment. *Short run*: sample ending in March 2022; *full window*: sample ending in September 2025; both start in January 2019. Standard errors clustered by destination $\times$ origin in parentheses, conditional on $\hat{\kappa}$. [†]Pre-war vessel share below 5%: these sections have almost no maritime margin to reallocate, and their estimates are imprecise and not interpreted. Arms (XIX) and art (XXI) are excluded because of negligible trade.

7. Discussion and Conclusion

This paper estimates the elasticity of substitution between maritime and land transport, a parameter that governs how much trade an economy preserves when its dominant shipping corridor closes, and one rarely estimated directly. The Russian blockade of Ukraine's Black and Azov Sea ports supplies identifying variation of a kind otherwise unavailable: a large and sustained loss of maritime access, varying in intensity over time and applied differentially across spells according to pre-war port dependence. Combining monthly customs data at the product-origin-destination level for January 2019-September 2025 with conflict events near Ukrainian ports, and estimating the mapping from conflict intensity to relative sea-to-land freight costs, we recover the elasticity from the modal reallocation it induced.

Our preferred specification implies an elasticity of substitution of 2.25 for values and 2.36 for quantities, with a range of roughly 1.9 to 3.7 across the specifications in Table 5

under the binary exposure assumption.

This implied estimate of the elasticity of substitution between transportation modes is identified from relative quantities within a trade relationship, so the factory-gate price, the composite cost index, total demand, and the upper-tier elasticity cancel exactly, which is what makes it portable across models. It is estimated from export data recorded at the factory gate, so the estimating equation delivers $-\eta$ directly, whereas the same parameter enters a CIF or expenditure-share specification as $-(\eta - 1)$. And it is conditional on $\hat{\kappa}$, the estimated mapping from conflict intensity onto log relative transport costs. Because $\hat{\kappa}$ is estimated rather than assumed, it carries a standard error that we propagate into the implied elasticity. The resulting interval is materially wider than the clustered one, and on a two-sided test it just includes unity. We state the substitutability result as a one-sided test, rejecting $\eta \leq 1$ at the five per cent level in every baseline specification.

Choices that do not bear on identification leave the implied elasticity near this value, with the quantity counterpart within one standard error of the value estimate, indicating physical reallocation rather than repricing. Under the wide definition of transportation modes, sample and specification variation designed to separate maritime disruption from correlated production disruption keeps it between 1.9 and 2.9. Under the narrow definition, excluding base metals or controlling for general war intensity leaves it indistinguishable from one, so for base metals we cannot fully separate substitution from production loss. The implied elasticity is highest at the onset of the blockade, roughly 3.3 in the first two months, falls to about 2.3 by mid-2022 and remains broadly stable thereafter. Adjustment was front-loaded, and what subsequently unwound was the emergency reallocation rather than a durable shift in transport technology. The window contains further shocks, such as the Grain Initiative and its collapse, the unilateral corridor and the western border blockades, so the profile reflects the partial return of maritime access as much as any decay in substitution capacity. That is itself informative: it identifies the reversibility of modal shifts once the disrupted mode returns, an object the studies identified from disruptions that persist, cannot speak to.

An implied value of about 2.25 means modes are substitutes, imperfect but substantial ones: overland routes absorbed a meaningful part of the maritime disruption, although the land margin expanded by only about a quarter as much as maritime shipments fell. Composition matters as well as magnitude. Road crossings into the European Union were the primary margin of adjustment for grains and oilseeds, whereas rail carried more of the response for bulk industrial goods such as minerals and base metals.

Sectoral estimates do not rise monotonically in pre-war maritime dependence. The most sea-dependent sections are bulk agricultural commodities for which overland routes could absorb only part of the volume at comparable cost. They show full-window elasticities of about 2.0, above one but below the aggregate. Sections already shipping mostly overland before the war show mixed responses: some are indistinguishable from unity, while others with a non-trivial share of vessel-exposed spells respond strongly. The largest responses, 3.6 for minerals and 5.0 for base metals, come from the middle of the distribution, where both modes were genuinely available, although the base-metal estimate also reflects severe production losses. Most sections attenuate over the longer window, notably fats and oils (from 4.7 to 1.9) and minerals (from 7.4 to 3.6), consistent with partial maritime recovery under successive corridor arrangements. An aggregate value applied uniformly will misstate disruption at both ends of the distribution.

Our estimate is context-specific, and the context favours substitution: land borders with four EU member states and Moldova, an extensive road network, substantial pre-existing trucking capacity, and an accommodating EU policy environment. If substitution remains incomplete under these conditions, and does not strengthen over three and a half years, economies with fewer overland alternatives should expect less. For island economies such as Taiwan, or for landlocked economies dependent on a small number of transit corridors, the relevant elasticities are likely lower, not higher. In the limit the modal margin disappears altogether: where pipeline capacity falls far short of normal seaborne throughput, as it does for crude and LNG out of the Gulf, there is no alternative mode at scale, and adjustment must come through curtailed production and price rather than through reallocation across modes. Our estimate bounds what modal substitution can contribute, and that bound is informative only where an alternative mode exists at scale, as it did in Ukraine.

Two implications follow from the level of the parameter rather than from the Ukrainian narrative. First, transport-mode and product diversification are complementary rather than substitutable forms of resilience. Even with an elasticity above two, the land margin offset only about a quarter of the maritime decline, leaving most disrupted trade unreplaced, so a product-diversified exporter whose entire basket moves through a single corridor remains exposed to a large part of that corridor's importance.

Second, the time profile bears on infrastructure appraisal. If substitution capacity grew with time, the case for maintaining redundancy *ex ante* would be weaker, since adaptation would eventually do the work. We find the opposite. The implied elasticity is highest at the moment of disruption, roughly 3.3 in the first two months, and lower

over every longer window, at about 2.3-2.5. Part of that decline reflects the partial return of maritime access rather than any decay in overland capability, so the profile bounds rather than measures the scope for adjustment at this horizon. But under either reading, modal reallocation behaves as an emergency response that partly reverses once the disrupted corridor reopens, not as a capability that accumulates through use. The social value of alternative transport infrastructure is therefore understated twice over when assessed by normal-time freight volumes: once because the alternative sits idle in normal times, and again because the capacity to switch does not build up on its own. Estimated mode-substitution elasticities make that comparison quantitative, corridor by corridor and sector by sector.

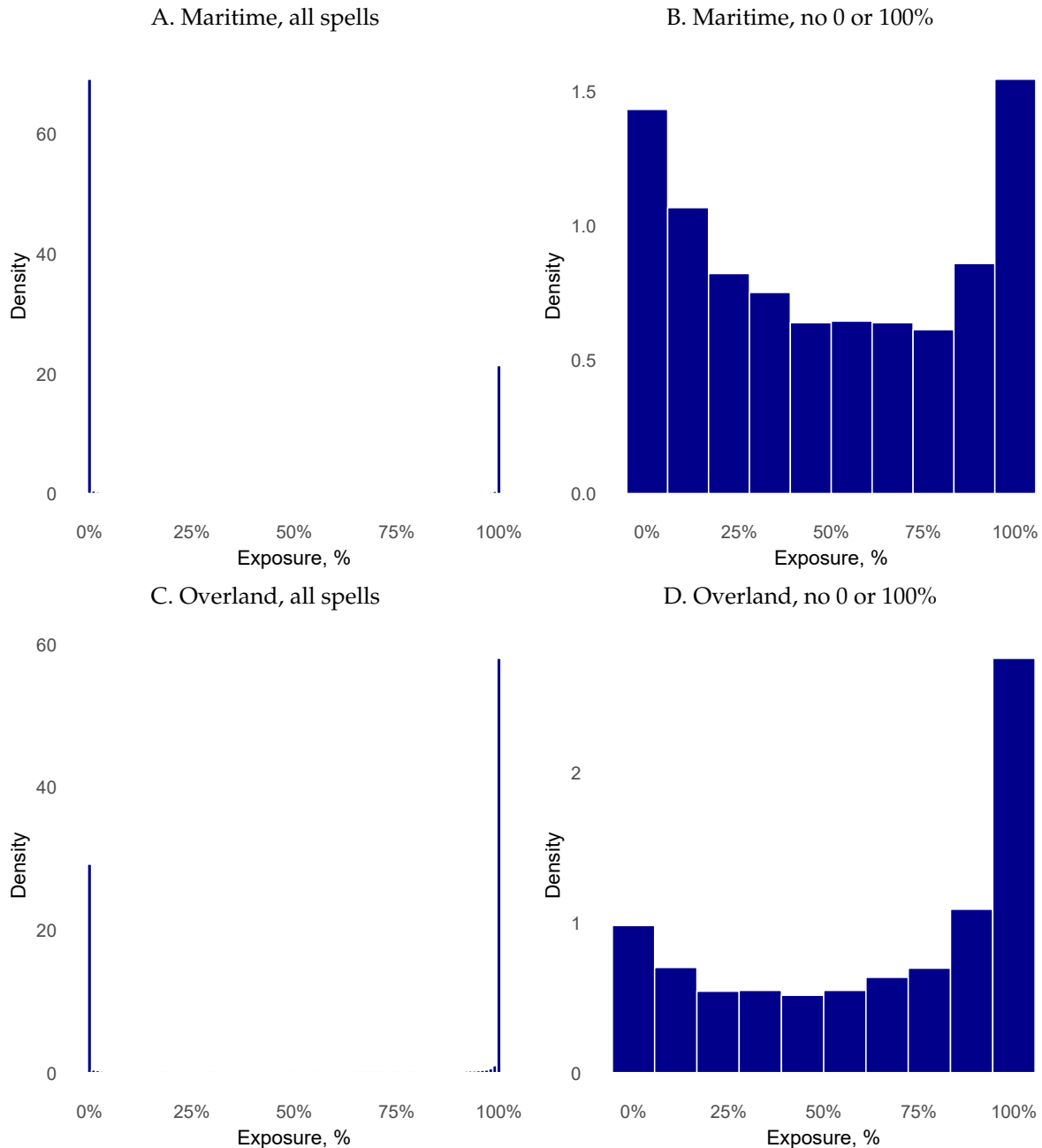
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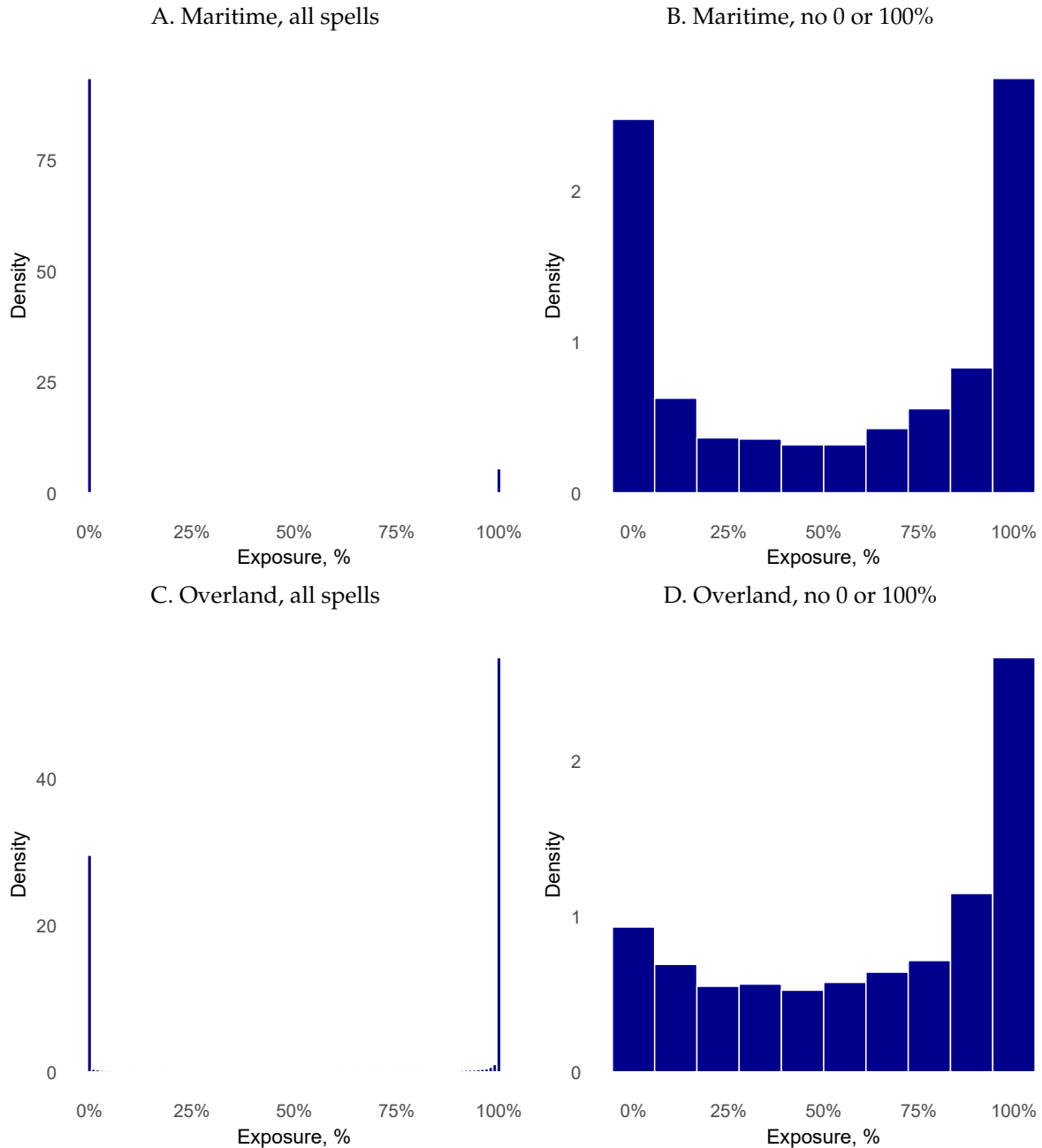
Appendix A. Additional Figures

FIGURE A.1. Distribution of export spells by exposure to transportation modes, % of total value (restricted sample, wide definitions of modes)



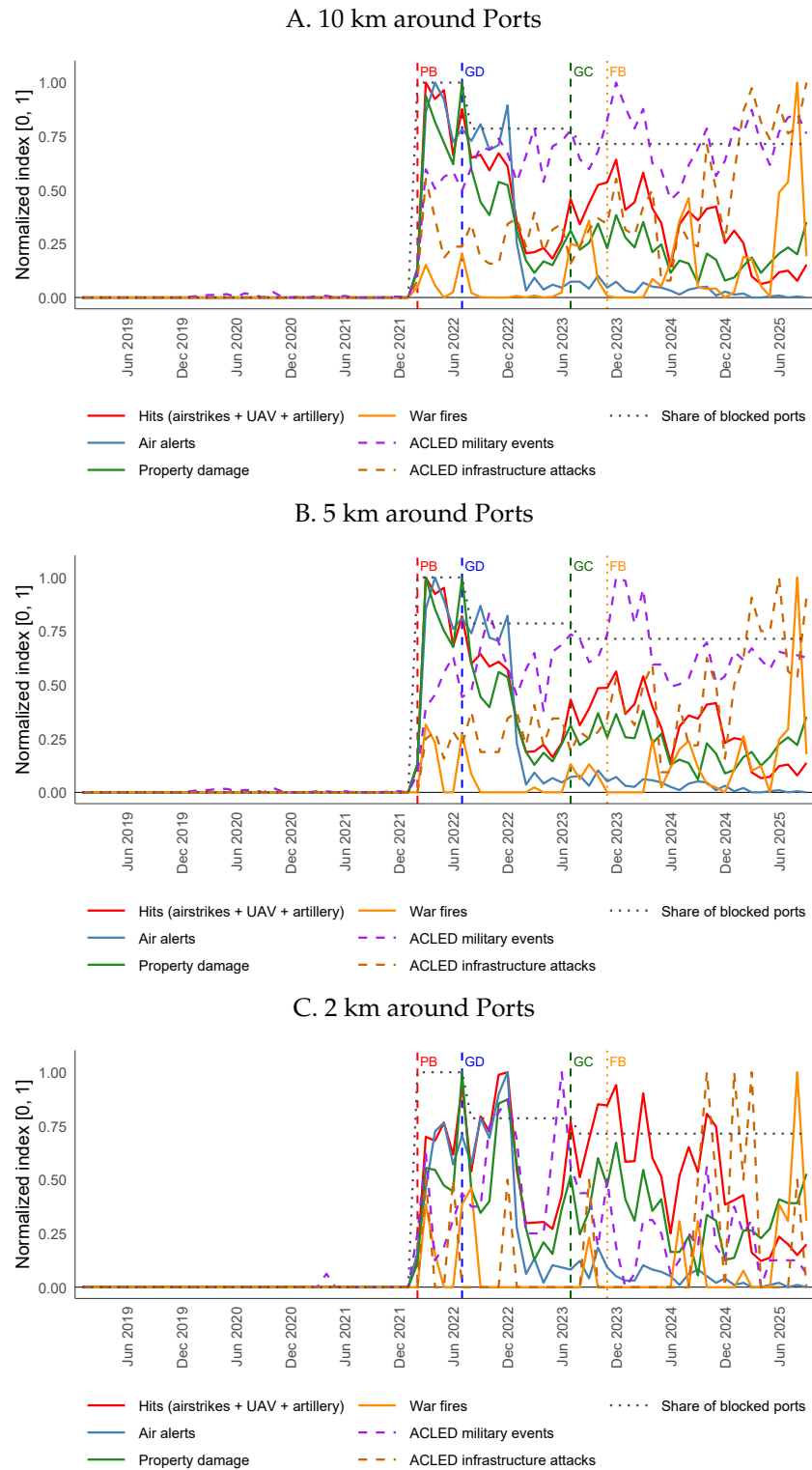
Note: Each observation is a product-destination-origin spell in the estimation sample (one per spell). Exposure is the pre-war (2019-2021) share of the spell's total export value shipped by sea (Panels A-B) or overland, by truck or railway (Panels C-D). Wide mode definitions, which include compound intermodal declarations. Panels A and C show all spells (101 bins, one per percentage point); Panels B and D exclude spells at exactly 0% or 100% (10 bins).

FIGURE A.2. Distribution of export spells by exposure to transportation modes, % of total value (restricted sample, narrow definitions of modes)



Note: Each observation is a product-destination-origin spell in the estimation sample (one per spell). Exposure is the pre-war (2019-2021) share of the spell's total export value shipped by sea (Panels A-B) or overland, by truck or railway (Panels C-D). Narrow mode definitions, which retain only single-mode customs declarations. Panels A and C show all spells (101 bins, one per percentage point); Panels B and D exclude spells at exactly 0% or 100% (10 bins).

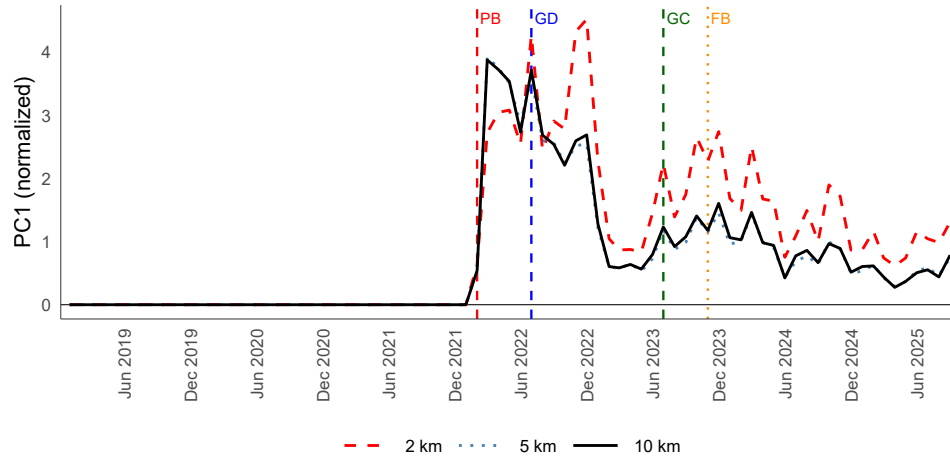
FIGURE A.3. War-related Events in Ukrainian Ports (Index)



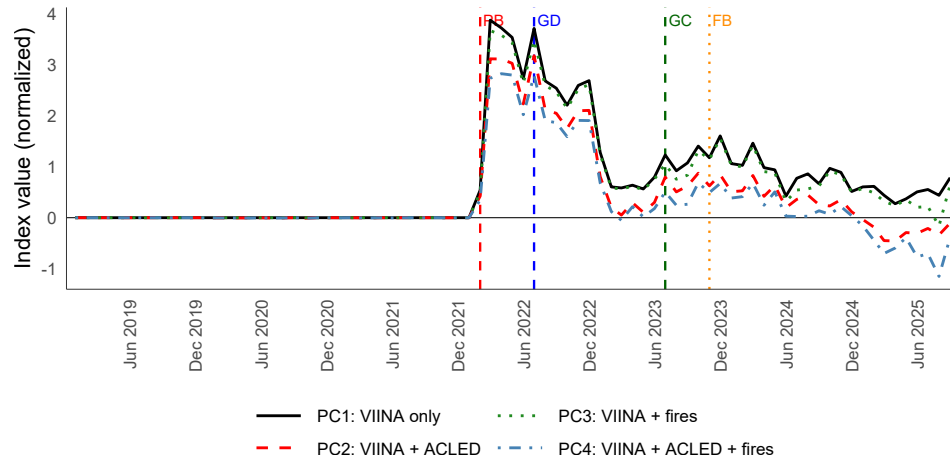
Note: Monthly war-related events within 10, 5 and 2 km of Ukraine's 18 Black Sea and Sea of Azov ports, each series min-max normalised to [0, 1]. Sources: VIINA 2.0 (hits, air alerts, property damage), *The Economist* (war fires) and ACLED (military events, infrastructure attacks). The dotted line is the share of ports closed and enters no index. Vertical markers as in Figure 3.

FIGURE A.4. Proxies of Port Blockade

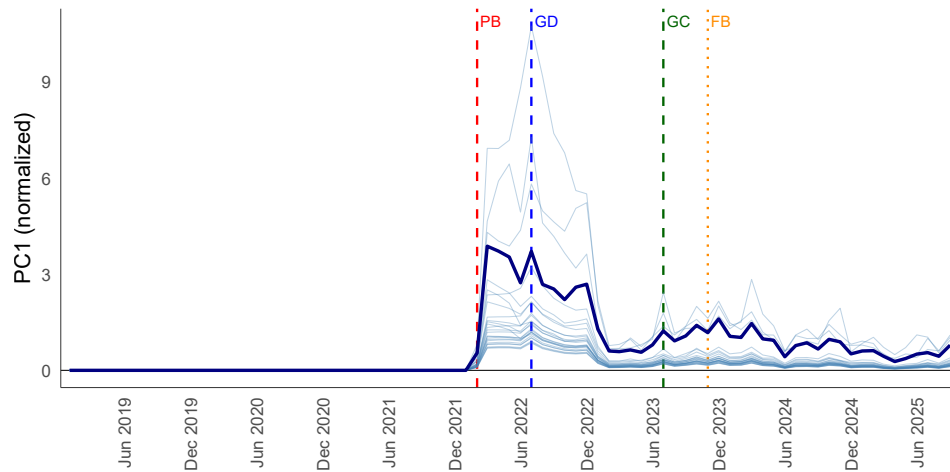
A. PC1 at the country level, different radii



B. Four instruments at the country level

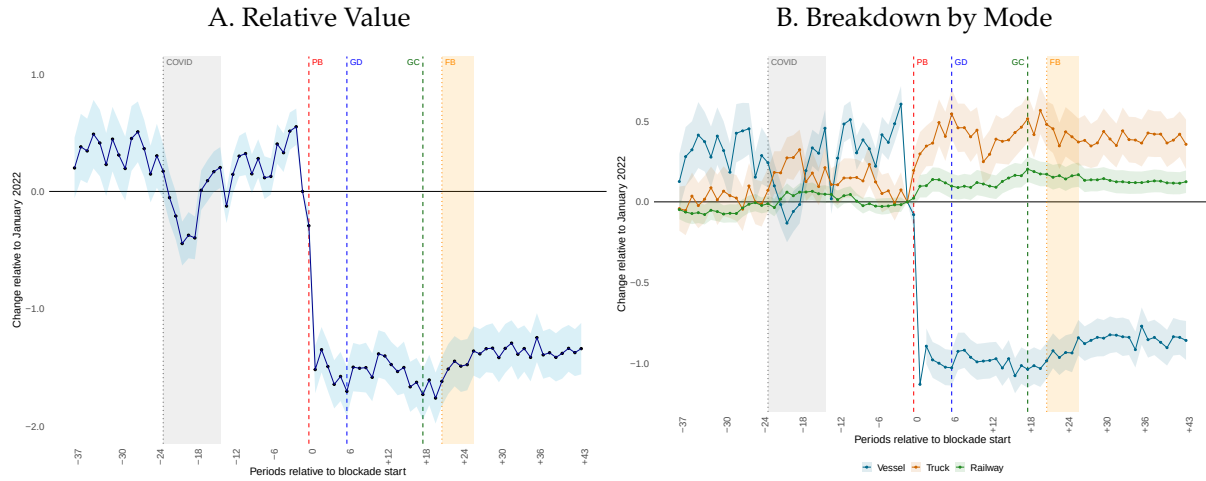


C. Distribution of regional PC1 (10 km)



Note: Panels A-B: country-level port-blockade indices, events deduplicated across overlapping port buffers and PCA fitted on post-invasion months; Panel A shows PC1 at 2, 5 and 10 km, Panel B the four indices at 10 km. Panel C: oblast-level PC1 at 10 km (light lines) against the country-level series (dark line). All indices are zero before February 2022 and measured in post-invasion standard deviations. Country-level series are descriptive and enter no estimation. Vertical markers as in Figure 3.

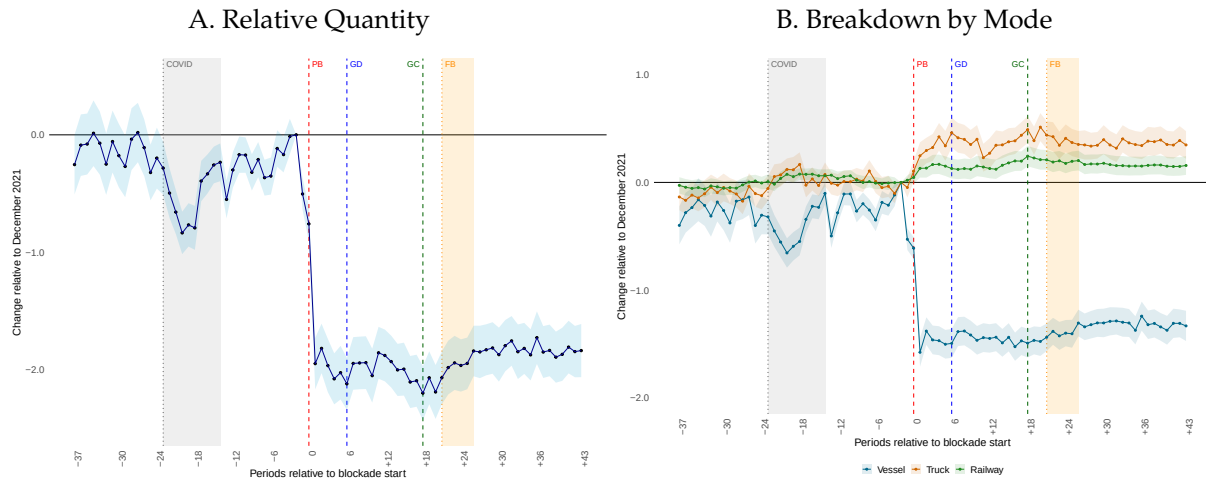
FIGURE A.5. Event Study: Relative Value with January 2022 as a Reference Period



Note: each figure plots coefficients from the event-study as in (13). Maritime relative to land transportation is expressed as $\text{arcsinh}(X_{iodt}^{\text{Maritime}}) - \text{arcsinh}(X_{iodt}^{\text{Land}})$, where X_{iodt}^k is exports value of product i shipped with transportation mode m from the origin oblast o to the destination country d . In Panel B, we report how each mode performed relative to the reference period. Standard errors are clustered by origin-destination combinations.

Timing key: COVID = COVID, Mar 2020; PB = start of port blockade, Feb 2022; GD = Black Sea Grain Initiative / Grain Deal, Jul 2022; GC = Ukrainian Black Sea Grain Corridor, Aug 2023; FB = Polish farmers and truckers/border blockade, Nov 2023–early 2024.

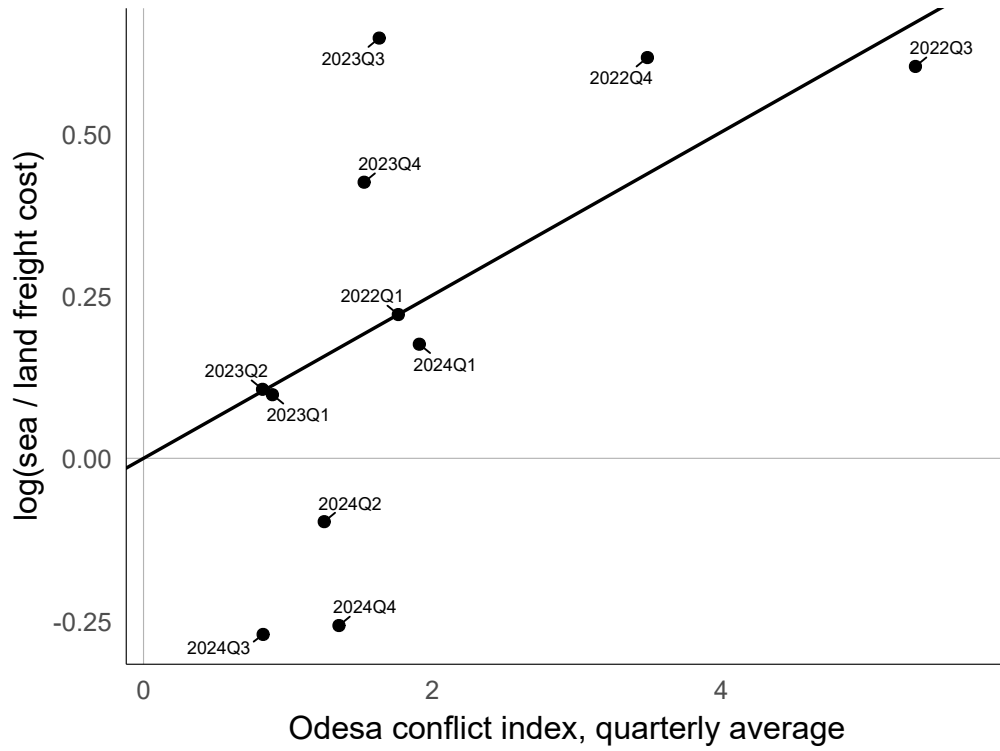
FIGURE A.6. Event Study: Relative Quantity



Note: each figure plots coefficients from the event-study as in (13). Maritime relative to land transportation is expressed as $\text{arcsinh}(Q_{iodt}^{\text{Maritime}}) - \text{arcsinh}(Q_{iodt}^{\text{Land}})$, where Q_{iodt}^k is exports quantity of product i shipped with transportation mode m from the origin oblast o to the destination country d . In Panel B, we report how each mode performed relative to the reference period. Standard errors are clustered by origin-destination combinations.

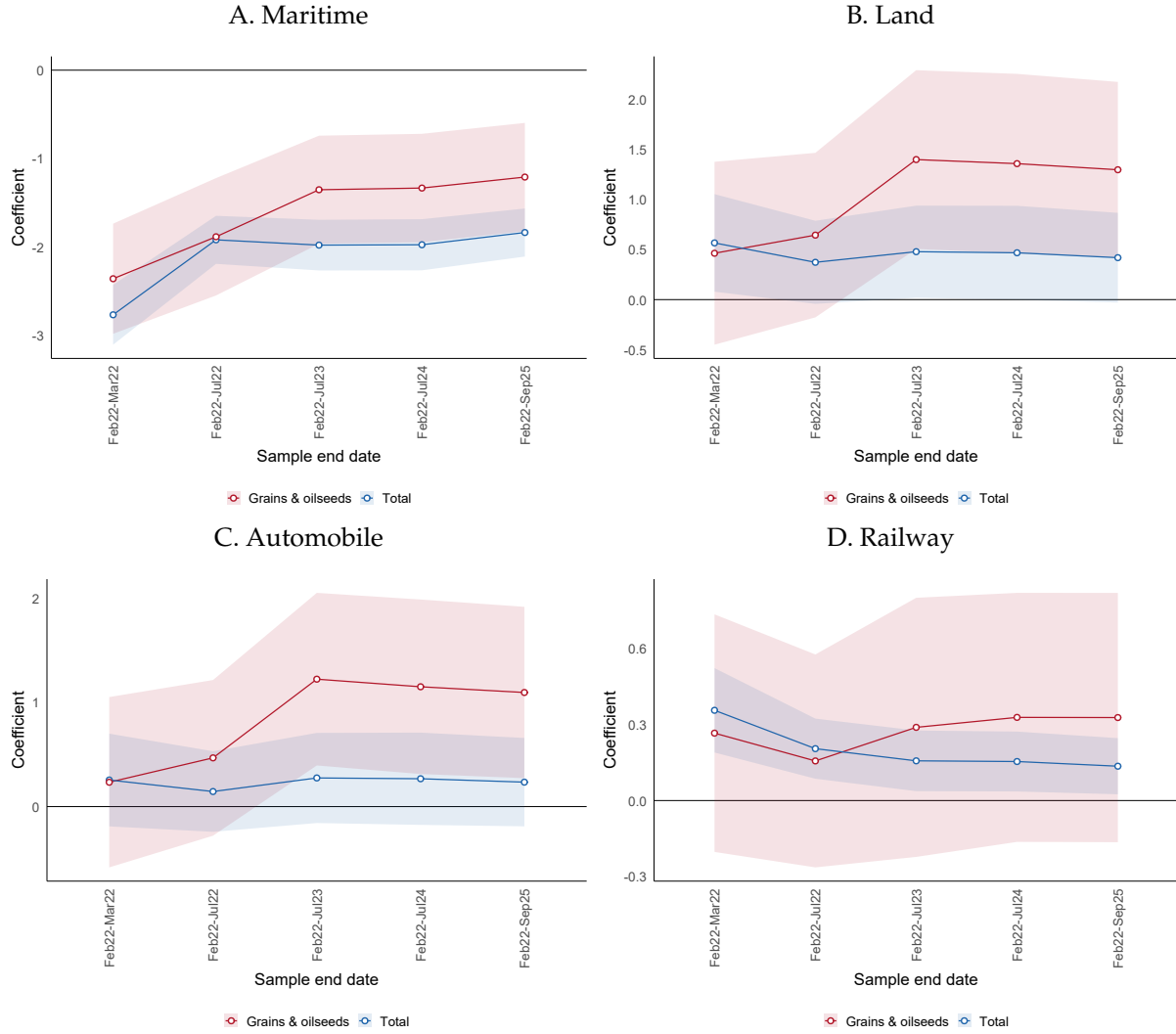
Timing key: COVID = COVID, Mar 2020; PB = start of port blockade, Feb 2022; GD = Black Sea Grain Initiative / Grain Deal, Jul 2022; GC = Ukrainian Black Sea Grain Corridor, Aug 2023; FB = Polish farmers and truckers/border blockade, Nov 2023–early 2024.

FIGURE A.7. First Stage Fit



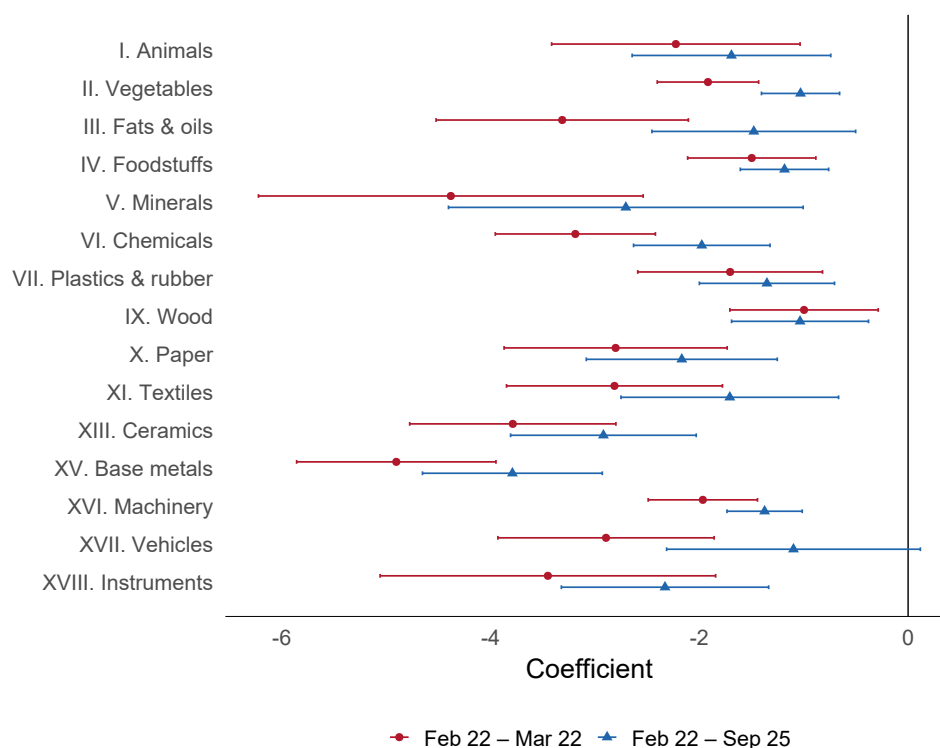
Note: Each point is a post-invasion calendar quarter. The vertical axis is $\log(\tau_q^{\text{sea}} / \tau_q^{\text{land}})$, the log ratio of the sea freight index to the value-weighted average of the road and rail indices ($\omega_R = 0.328$), all rebased to 2021Q4 = 100 (equation (1)). The horizontal axis is the baseline conflict index, PC1 at the 10 km radius, averaged over the three months of the quarter for Odesa oblast. The line is the through-origin fit of equation (11) over the eleven post-invasion quarters, with slope $\hat{\kappa} = 0.126$ (standard error 0.034). The restriction normalises the relative cost change to zero in the last pre-invasion quarter, when the conflict index is zero by construction; the intercept of the unrestricted regression is -0.098 ($p = 0.51$), so the data do not reject it. No sea rate is quoted for 2022Q2, when the benchmark route was closed, so that quarter is absent.

FIGURE A.8. Short vs. Long-run Effects: Contribution of Modes



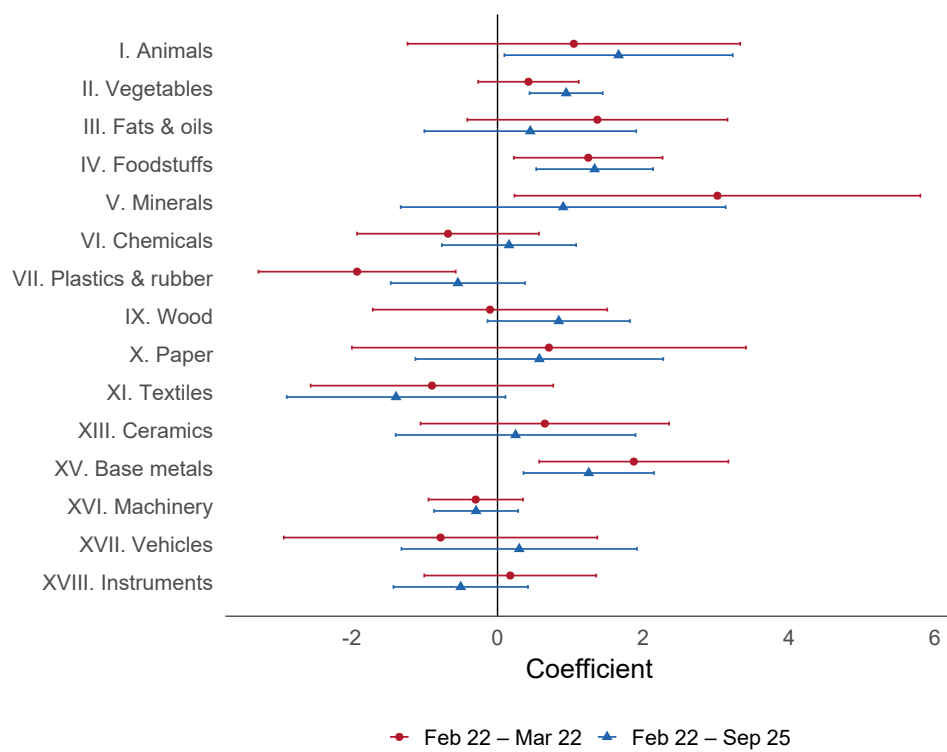
Note: Coefficients on $E_{iod} \times \tilde{Z}_{ot}$ from equation (14) with the baseline fixed effects, estimated separately for each mode on export values: arsinh of vessel (Panel A), overland (Panel B), truck (Panel C) and railway (Panel D) exports. Samples start in January 2019 and end at the indicated month. *Total* uses all products; *Grains & oilseeds* restricts the sample to HS chapters 10 and 12. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by κ . Shaded bands are 95% confidence intervals based on standard errors clustered by destination $\times$ origin and conditional on κ .

FIGURE A.9. Sectoral short-run and long-run responses: Maritime



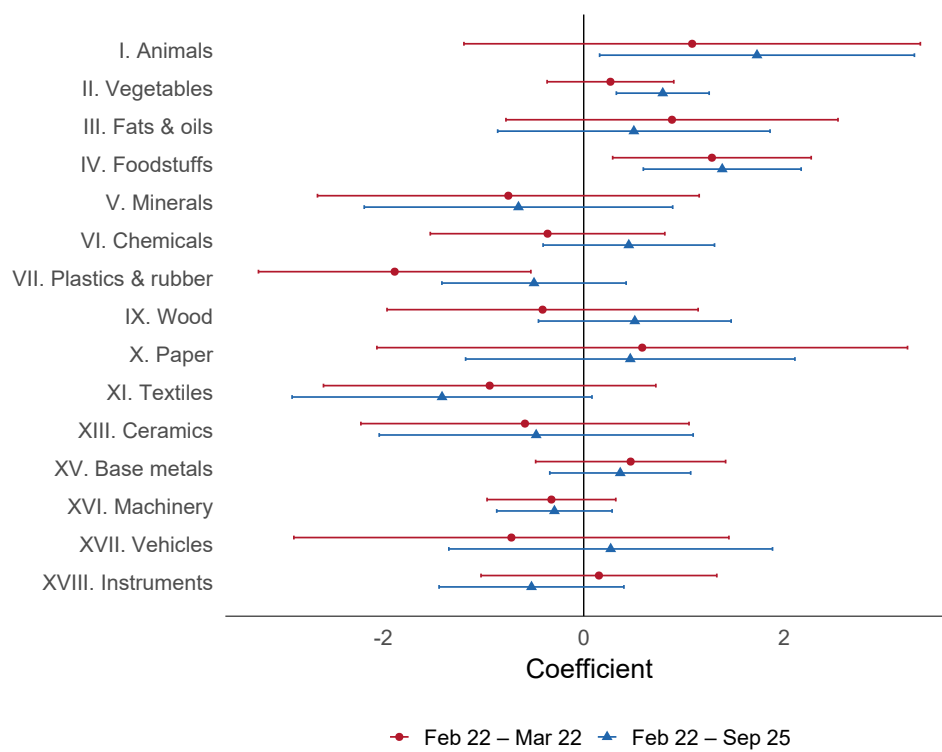
Note: Coefficients on $E_{iod} \times \tilde{Z}_{ot}$ from equation (14), estimated separately for each HS section on export values with the baseline fixed effects, exposure and port-blockade index (PC1, 10 km, scaled by $\hat{\kappa}$). The outcome is $\text{arsinh}(X_{iod}^M)$, vessel exports. Circles: samples ending in March 2022 (short run); triangles: samples ending in September 2025 (full window); all samples start in January 2019. Horizontal bars are 95% confidence intervals based on standard errors clustered by destination $\times$ origin and conditional on $\hat{\kappa}$. Sections with a pre-war vessel share of export value below 5% are omitted.

FIGURE A.10. Sectoral short-run and long-run responses: Overland



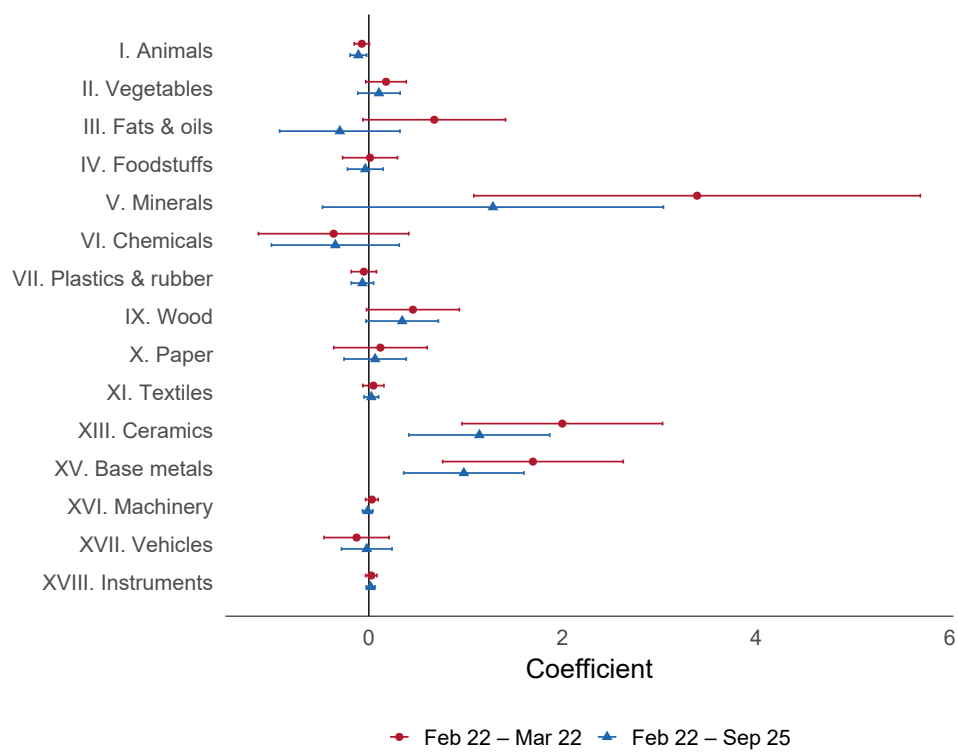
Note: As Figure A.9, with $\text{arsinh}(X_{iod}^L)$, overland (truck and railway) exports, as the outcome.

FIGURE A.11. Sectoral short-run and long-run responses: Automobile



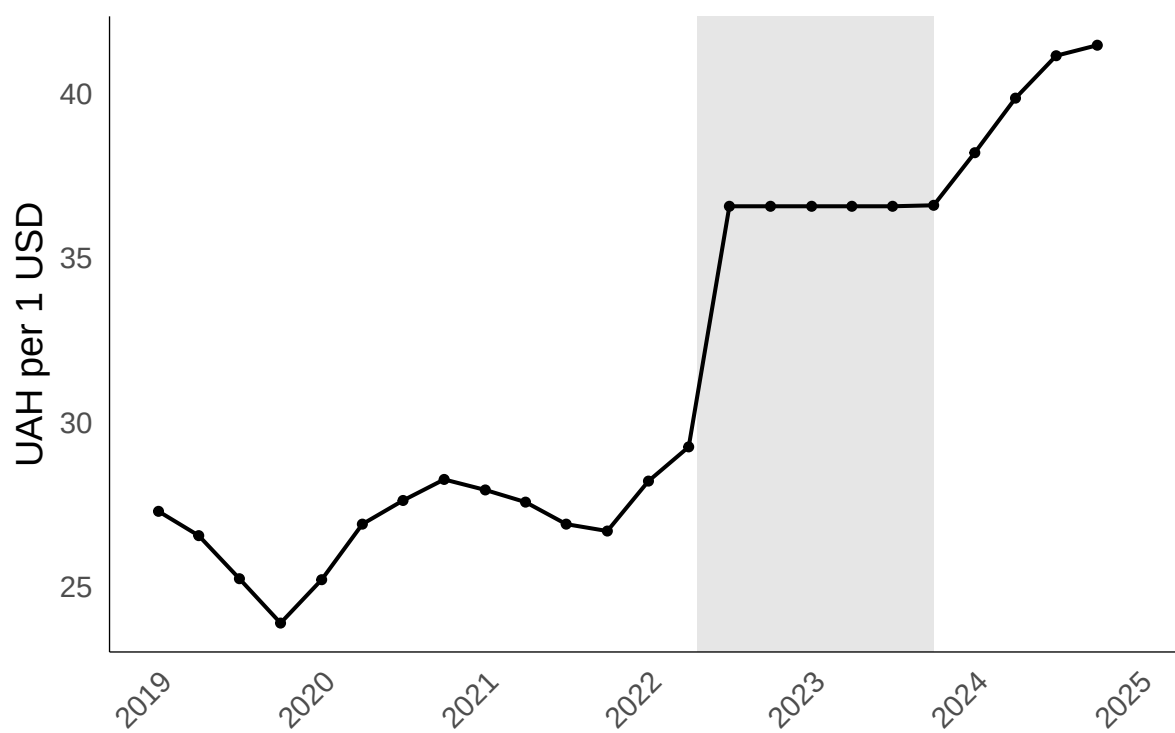
Note: As Figure A.9, with $\text{arsinh}(X_{ioid}^A)$, truck exports, as the outcome.

FIGURE A.12. Sectoral short-run and long-run responses: Railway



Note: As Figure A.9, with $\text{arsinh}(X_{i0d}^R)$, railway exports, as the outcome.

FIGURE A.13. UAH/USD official NBU rate.



Source: National Bank of Ukraine (NBU) rate

Appendix B. Additional Tables

TABLE A1. Sensitivity: Baseline with Physical Quantities

Dependent Variables: Model:	$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$ (1) OLS	$\text{arsinh}(Q_{iod}^M)$ (2) OLS	$\text{arsinh}(Q_{iod}^L)$ (3) OLS	Q_{iod}^M (4) Poisson	Q_{iod}^L (5) Poisson
<i>Variables</i>					
$E_{iod} \times \tilde{Z}_{ot}$	-2.363*** (0.289)	-1.728*** (0.132)	0.635*** (0.205)	-0.478 (0.414)	1.282*** (0.475)
<i>Fixed-effects</i>					
Product×Destination×Origin	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓
<i>Fit statistics</i>					
Observations	5,939,649	5,939,649	5,939,649	1,400,041	4,257,480
R ²	0.49047	0.37932	0.52601	0.88122	0.94493

Note: All specifications follow equation (14) and include product×destination×origin, product×period, destination×period, and origin×period fixed effects. Outcomes are physical export quantities under the wide definition of modes, which includes compound intermodal declarations. $\tilde{Z}_{ot}$ is the first principal component of VIINA 2.0 conflict events within 10 km of Ukrainian ports, scaled by $\hat{\kappa}$, the estimated slope of the log relative maritime-to-overland freight cost on the Odesa conflict index (Section 3.4), so the coefficient in column (1) equals $-\hat{\eta}$. E_{iod} is a pre-war (2019-2021) indicator for vessel use within a product-destination-origin spell. Column (1) reports the IHS difference between vessel and land trade; columns (2) and (3) the two margins separately; columns (4) and (5) the same margins by PPML. Columns (4) and (5) retain fewer observations because Poisson estimation drops fixed-effect groups whose outcome is zero throughout; the two margins are estimated on different samples and their difference has no structural interpretation. Standard errors clustered by destination×origin in parentheses and conditional on $\hat{\kappa}$. Sample: January 2019-September 2025. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

TABLE A2. Sensitivity: Baseline with FOB Values, Narrow Definitions of Modes

Dependent Variables: Model:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$ (1) OLS	$\text{arsinh}(X_{iod}^M)$ (2) OLS	$\text{arsinh}(X_{iod}^L)$ (3) OLS	X_{iod}^M (4) Poisson	X_{iod}^L (5) Poisson
<i>Variables</i>					
$E_{iod} \times \tilde{Z}_{ot}$	-1.999*** (0.262)	-1.747*** (0.199)	0.252 (0.190)	-1.463** (0.671)	0.249 (0.358)
<i>Fixed-effects</i>					
Product×Destination×Origin	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓
<i>Fit statistics</i>					
Observations	5,939,649	5,939,649	5,939,649	256,896	4,106,328
R ²	0.51064	0.40615	0.51288	0.79320	0.87176

Note: All specifications follow equation (14) and include product×destination×origin, product×period, destination×period, and origin×period fixed effects. Outcomes are FOB export values under the narrow definition of modes, which retains only single-mode customs declarations. $\tilde{Z}_{ot}$ is the first principal component of VIINA 2.0 conflict events within 10 km of Ukrainian ports, scaled by $\hat{\kappa}$, the estimated slope of the log relative maritime-to-overland freight cost on the Odesa conflict index (Section 3.4), so the coefficient in column (1) equals $-\hat{\eta}$. E_{iod} is a pre-war (2019–2021) indicator for vessel use within a product-destination-origin spell. Column (1) reports the IHS difference between vessel and land trade; columns (2) and (3) the two margins separately; columns (4) and (5) the same margins by PPML. Columns (4) and (5) retain fewer observations because Poisson estimation drops fixed-effect groups whose outcome is zero throughout; the two margins are estimated on different samples and their difference has no structural interpretation. Standard errors clustered by destination×origin in parentheses and conditional on $\hat{\kappa}$. Sample: January 2019–September 2025. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

TABLE A3. Sensitivity: Baseline with Quantities, Narrow Definitions of Modes

Dependent Variables: Model:	$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$ (1) OLS	$\text{arsinh}(Q_{iod}^M)$ (2) OLS	$\text{arsinh}(Q_{iod}^L)$ (3) OLS	Q_{iod}^M (4) Poisson	Q_{iod}^L (5) Poisson
<i>Variables</i>					
$E_{iod} \times \tilde{Z}_{ot}$	-2.027*** (0.262)	-1.678*** (0.200)	0.349* (0.197)	-0.803* (0.485)	1.251** (0.524)
<i>Fixed-effects</i>					
Product×Destination×Origin	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓
<i>Fit statistics</i>					
Observations	5,939,649	5,939,649	5,939,649	256,902	4,102,655
R ²	0.52410	0.40713	0.53361	0.83345	0.94732

Note: All specifications follow equation (14) and include product×destination×origin, product×period, destination×period, and origin×period fixed effects. Outcomes are physical export quantities under the narrow definition of modes, which retains only single-mode customs declarations. $\tilde{Z}_{ot}$ is the first principal component of VIINA 2.0 conflict events within 10 km of Ukrainian ports, scaled by $\hat{\kappa}$, the estimated slope of the log relative maritime-to-overland freight cost on the Odesa conflict index (Section 3.4), so the coefficient in column (1) equals $-\hat{\eta}$. E_{iod} is a pre-war (2019–2021) indicator for vessel use within a product-destination-origin spell. Column (1) reports the IHS difference between vessel and land trade; columns (2) and (3) the two margins separately; columns (4) and (5) the same margins by PPML. Columns (4) and (5) retain fewer observations because Poisson estimation drops fixed-effect groups whose outcome is zero throughout; the two margins are estimated on different samples and their difference has no structural interpretation. Standard errors clustered by destination×origin in parentheses and conditional on $\hat{\kappa}$. Sample: January 2019–September 2025. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

TABLE A4. Aggregate Implied Elasticity under Different Specifications: Quantities

Dependent Variables:	$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$							
Model:	Baseline (1)	Cont. expo. (2)	5 km (3)	2 km (4)	PC2 (5)	PC3 (6)	PC4 (7)	Excl. RU, BY (8)
<i>Variables</i>								
$E_{iod} \times \bar{Z}_{ot}$	-2.363*** (0.289)	-3.222*** (0.321)	-2.631*** (0.344)	-2.806*** (0.517)	-3.517*** (0.433)	-2.933*** (0.347)	-3.796*** (0.455)	-2.456*** (0.312)
<i>Fixed-effects</i>								
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>								
Observations	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,939,649	5,296,347
R ²	0.49047	0.49065	0.49049	0.49043	0.49064	0.49056	0.49069	0.49468

Note: All columns estimate equation (14) on export quantities with wide definition of modes and the baseline fixed effects; the outcome is $\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$. Column (1) is the baseline: binary pre-war vessel exposure and PC1 of VIINA 2.0 events within 10 km of ports. Each remaining column changes one element. Column (2) replaces the binary exposure with the pre-war vessel share of spell export quantity. Columns (3)-(4) count conflict events within 5 and 2 km of ports. Columns (5)-(7) use alternative indices: PC2 adds ACLED events, PC3 adds war-related fires, and PC4 adds all three sources. Column (8) excludes exports to Russia and Belarus. Each index is scaled by its own $\hat{\kappa}$ (Section 3.4), so the coefficients equal $-\hat{\eta}$. Standard errors clustered by destination×origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A5. The Role of Multimodality: Results for Values by Distance

Dependent Variables:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$			$\text{arsinh}(X_{iod}^M)$			$\text{arsinh}(X_{iod}^L)$		
Distance:	< 1500	1500–3000	> 3000	< 1500	1500–3000	> 3000	< 1500	1500–3000	> 3000
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Variables</i>									
$E_{iod} \times \bar{Z}_{ot}$	-1.179** (0.4680)	-4.101*** (0.4692)	-2.515*** (0.3522)	-1.043*** (0.2664)	-2.567*** (0.2844)	-2.202*** (0.2512)	0.1361 (0.3125)	1.533*** (0.2296)	0.3126 (0.2447)
<i>Fixed-effects</i>									
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>									
Observations	3,425,652	1,269,027	1,244,970	3,425,652	1,269,027	1,244,970	3,425,652	1,269,027	1,244,970
R ²	0.50527	0.46673	0.36166	0.41229	0.40410	0.37447	0.51623	0.50517	0.40475

Note: All columns estimate equation (14) on export values with the baseline fixed effects, splitting the sample by the distance between Ukraine and the destination country: short ($d < 1,500$ km), medium ($1,500 \leq d \leq 3,000$ km) and long ($d > 3,000$ km). Columns (1)-(3) report the IHS difference between vessel and land values, whose coefficient equals $-\hat{\eta}$; columns (4)-(6) the vessel margin and columns (7)-(9) the land margin. $\bar{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019-2021) indicator for vessel use within the spell. Standard errors clustered by destination×origin in parentheses, conditional on $\hat{\kappa}$. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A6. The Role of Multimodality: Results for Quantities by Distance

Dependent Variables:	$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$			$\text{arsinh}(Q_{iod}^M)$			$\text{arsinh}(Q_{iod}^L)$		
Distance:	< 1500	1500–3000	> 3000	< 1500	1500–3000	> 3000	< 1500	1500–3000	> 3000
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Variables</i>									
$E_{iod} \times \tilde{Z}_{ot}$	-1.362*** (0.4491)	-3.913*** (0.4467)	-2.259*** (0.3161)	-1.011*** (0.2676)	-2.402*** (0.2662)	-1.859*** (0.2168)	0.3506 (0.2937)	1.511*** (0.2179)	0.3998** (0.1995)
<i>Fixed-effects</i>									
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>									
Observations	3,425,652	1,269,027	1,244,970	3,425,652	1,269,027	1,244,970	3,425,652	1,269,027	1,244,970
R ²	0.52141	0.46594	0.35104	0.42532	0.40952	0.38291	0.53685	0.51684	0.38697

Note: All columns estimate equation (14) on export quantities with the baseline fixed effects, splitting the sample by the distance between Ukraine and the destination country: short ($d < 1,500$ km), medium ($1,500 \leq d \leq 3,000$ km) and long ($d > 3,000$ km). Columns (1)-(3) report the IHS difference between vessel and land values, whose coefficient equals $-\hat{\eta}$; columns (4)-(6) the vessel margin and columns (7)-(9) the land margin. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019-2021) indicator for vessel use within the spell. Standard errors clustered by destination×origin in parentheses, conditional on $\hat{\kappa}$. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A7. Production Compounds: Narrow Origin × HS Chapter Cells

Dependent Variable:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$	
Definitions of modes:	Wide	Narrow	Wide	Narrow
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
$E_{iod} \times \tilde{Z}_{ot}$	-2.873*** (0.3281)	-2.648*** (0.2580)	-2.943*** (0.3061)	-2.671*** (0.2705)
<i>Fixed-effects</i>				
Product×Destination×Origin	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓
Origin×HS Chapter×Period	✓	✓	✓	✓
<i>Fit statistics</i>				
Observations	5,867,883	5,867,883	5,867,883	5,867,883
R ²	0.49583	0.52410	0.50345	0.53673

Note: All columns estimate equation (14) with the origin×period fixed effects of the baseline replaced by origin×HS chapter×period fixed effects, which absorb any shock to a two-digit HS chapter in a given oblast and month, including sector-specific production disruption. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019-2021) indicator for vessel use within the spell, so the coefficient equals $-\hat{\eta}$. Columns (1)-(2) use export values and columns (3)-(4) quantities; wide modes sum truck and railway into land, narrow modes retain single-mode declarations only. The sample is smaller than in Table 3 because products without an assigned HS chapter are excluded. Standard errors clustered by destination×origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A8. Excluding the Most Disrupted Sector

Dependent Variable:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$		$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$	
Sectors:	All		All		Excluding metallurgy		Excluding metallurgy	
Definitions of modes:	Wide	Narrow	Wide	Narrow	Wide	Narrow	Wide	Narrow
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
$E_{iod} \times \tilde{Z}_{ot}$	-2.254*** (0.3127)	-1.999*** (0.2616)	-2.363*** (0.2889)	-2.027*** (0.2624)	-1.972*** (0.2927)	-1.245*** (0.2329)	-2.073*** (0.2683)	-1.211*** (0.2271)
<i>Fixed-effects</i>								
Product $\times$ Destination $\times$ Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>								
Observations	5,939,649	5,939,649	5,939,649	5,939,649	5,304,690	5,304,690	5,304,690	5,304,690
R ²	0.48209	0.51064	0.49047	0.52410	0.48198	0.51194	0.49173	0.52792

Note: All columns estimate equation (14) with the baseline fixed effects. Columns (1)-(4) use the full estimation sample; columns (5)-(8) exclude base metals and articles of base metal (HS chapters 72-83, Section XV), the sector most directly affected by wartime production losses. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019-2021) indicator for vessel use within the spell, so the coefficient equals $-\hat{\eta}$. Wide modes sum truck and railway into land; narrow modes retain single-mode declarations only. Standard errors clustered by destination $\times$ origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A9. Keeping Only Oblasts Farther from the Front Line

Dependent Variable:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$		$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$	
Including Kyiv city:	Yes		Yes		No		No	
Definitions of modes:	Wide	Narrow	Wide	Narrow	Wide	Narrow	Wide	Narrow
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Variables</i>								
$E_{iod} \times \tilde{Z}_{ot}$	-2.391*** (0.5031)	-2.139*** (0.3502)	-2.483*** (0.4493)	-2.091*** (0.3298)	-2.104*** (0.3955)	-2.069*** (0.3272)	-2.159*** (0.3708)	-2.005*** (0.3150)
<i>Fixed-effects</i>								
Product $\times$ Destination $\times$ Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin $\times$ Period	✓	✓	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>								
Observations	3,980,097	3,980,097	3,980,097	3,980,097	2,835,243	2,835,243	2,835,243	2,835,243
R ²	0.50227	0.52997	0.51218	0.54609	0.51583	0.53973	0.52330	0.55240

Note: All columns estimate equation (14) with the baseline fixed effects, on spells originating outside the oblasts closest to the front line: Donetsk, Luhansk, Zaporizhzhia, Kherson, Kharkiv, Sumy, Chernihiv, Mykolaiv and Kyiv oblast are excluded. Columns (5)-(8) additionally exclude Kyiv city, the dominant customs-clearance hub. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019–2021) indicator for vessel use within the spell, so the coefficient equals $-\hat{\eta}$. Columns (1)-(2) and (5)-(6) use export values, the remaining columns quantities; wide modes sum truck and railway into land, narrow modes retain single-mode declarations only. Standard errors clustered by destination $\times$ origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A10. Excluding Oblasts One-by-One

Code	Origin dropped	Wide / Value	Narrow / Value	Wide / Qty	Narrow / Qty
5	Vinnytsia	2.214***	1.986***	2.326***	2.017***
7	Volyn	2.260***	2.036***	2.363***	2.062***
12	Dnipropetrovsk	2.083***	1.797***	2.189***	1.805***
14	Donetsk	2.115***	1.674***	2.231***	1.677***
18	Zhytomyr	2.222***	1.981***	2.333***	2.005***
21	Zakarpattia	2.228***	2.010***	2.341***	2.041***
23	Zaporizhzhia	2.082***	1.716***	2.191***	1.715***
26	Ivano-Frankivsk	2.219***	1.965***	2.335***	1.995***
32	Kyiv oblast	2.174***	2.018***	2.286***	2.042***
35	Kirovohrad	2.223***	1.984***	2.335***	2.006***
44	Luhansk	2.252***	2.001***	2.359***	2.026***
46	Lviv	2.202***	1.987***	2.320***	2.019***
48	Mykolaiv	3.041***	3.117***	3.151***	3.203***
51	Odesa	3.399***	2.402***	3.469***	2.559***
53	Poltava	2.227***	1.966***	2.332***	1.986***
56	Rivne	2.245***	1.991***	2.349***	2.017***
59	Sumy	2.225***	1.979***	2.326***	2.000***
61	Ternopil	2.233***	2.000***	2.346***	2.031***
63	Kharkiv	2.214***	2.013***	2.303***	2.030***
65	Kherson	2.258***	1.934***	2.361***	1.959***
68	Khmelnyskyi	2.224***	1.996***	2.333***	2.024***
71	Cherkasy	2.211***	1.976***	2.320***	2.001***
73	Chernivtsi	2.234***	1.998***	2.343***	2.026***
74	Chernihiv	2.231***	1.998***	2.343***	2.024***
80	Kyiv city	2.098***	2.013***	2.196***	2.034***
	Pooled	2.254***	1.999***	2.363***	2.027***

Note: Each row re-estimates equation (14) with the baseline fixed effects, dropping all spells from the indicated origin oblast (oblast codes follow KOATUU). Entries are implied elasticities $\hat{\eta} = -\hat{\beta}$. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\bar{K}$, and E_{iod} is the pre-war (2019-2021) indicator for vessel use within the spell. Wide modes sum truck and railway into land; narrow modes retain single-mode declarations only. Standard errors clustered by destination $\times$ origin. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A11. Impact of Pre-War Storage, Value

Dependent Variable:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$					
Period:	Short run		Storage		Long run	
Products:	All	Agri	All	Agri	All	Agri
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
$E_{iod} \times \tilde{Z}_{ot}$	-3.331*** (0.3444)	-2.624*** (0.6394)	-2.602*** (0.3110)	-2.382*** (0.5569)	-2.254*** (0.3127)	-2.317*** (0.5072)
<i>Fixed-effects</i>						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
Observations	2,859,831	228,501	3,079,818	246,078	5,939,649	474,579
R ²	0.56772	0.48644	0.55109	0.47515	0.48209	0.42022

Note: All columns estimate equation (14) on export values with the baseline fixed effects. Each window starts in January 2019 and ends in March 2022 (short run), June 2022 (storage) or September 2025 (long run). Agri denotes HS chapters 10 (cereals), 11 (milling products), 12 (oilseeds) and 23 (food-industry residues and fodder). $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019–2021) indicator for vessel use within the spell, so the coefficient equals $-\hat{\eta}$. Standard errors clustered by destination×origin in parentheses. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A12. Impact of Pre-War Storage, Quantity

Dependent Variable:	$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$					
Period:	Short run		Storage		Long run	
Products:	All	Agri	All	Agri	All	Agri
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
$E_{iod} \times \tilde{Z}_{ot}$	-3.430*** (0.3097)	-2.873*** (0.6762)	-2.725*** (0.2874)	-2.600*** (0.5940)	-2.363*** (0.2889)	-2.542*** (0.5454)
<i>Fixed-effects</i>						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
Observations	2,859,831	228,501	3,079,818	246,078	5,939,649	474,579
R ²	0.57955	0.48550	0.56233	0.47412	0.49047	0.41782

Note: All columns estimate equation (14) on export quantities with the baseline fixed effects. Each window starts in January 2019 and ends in March 2022 (short run), June 2022 (storage) or September 2025 (long run). Agri denotes HS chapters 10 (cereals), 11 (milling products), 12 (oilseeds) and 23 (food-industry residues and fodder). $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$, and E_{iod} is the pre-war (2019–2021) indicator for vessel use within the spell, so the coefficient equals $-\hat{\eta}$. Standard errors clustered by destination×origin in parentheses. Signif. codes: *** 0.01, ** 0.05, * 0.1.

TABLE A13. Controlling for General War Intensity

Dependent Variable:	$\text{arsinh}(X_{iod}^M) - \text{arsinh}(X_{iod}^L)$		$\text{arsinh}(Q_{iod}^M) - \text{arsinh}(Q_{iod}^L)$	
Definitions of modes:	Wide	Narrow	Wide	Narrow
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
$E_{iod} \times \tilde{Z}_{ot}$	-1.910*** (0.2981)	-1.521*** (0.2487)	-2.018*** (0.2737)	-1.522*** (0.2457)
$E_{iod} \times \text{ACLED}$	-0.5271*** (0.0579)	-0.6841*** (0.0805)	-0.5271*** (0.0549)	-0.7234*** (0.0812)
$E_{iod} \times \text{Fires}$	-0.0379*** (0.0082)	-0.0775*** (0.0103)	-0.0437*** (0.0075)	-0.0811*** (0.0106)
<i>Fixed-effects</i>				
Product×Destination×Origin	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓
<i>Fit statistics</i>				
Observations	5,939,649	5,939,649	5,939,649	5,939,649
R ²	0.48270	0.51123	0.49119	0.52489

Note: All columns estimate equation (14) with the baseline fixed effects, adding interactions of pre-war maritime exposure E_{iod} with two oblast-wide measures of general war intensity: ACLED events and war-related fires (The Economist and Solstad 2023), each counted across the entire oblast. These controls are not scaled by $\hat{\kappa}$, so only the coefficient on $E_{iod} \times \tilde{Z}_{ot}$ equals $-\hat{\eta}$. $\tilde{Z}_{ot}$ is the baseline port-blockade index (PC1, 10 km), scaled by $\hat{\kappa}$. Columns (1)-(2) use export values and columns (3)-(4) quantities; wide modes sum truck and railway into land, narrow modes retain single-mode declarations only. Standard errors clustered by destination×origin in parentheses. Sample: January 2019-September 2025. Signif. codes: *** 0.01, ** 0.05, * 0.1.

Appendix C. Details on Data

C.1. Recoding transportation modes

Original data comes with a more detailed breakdown of trade flows into transportation modes. In order to facilitate analysis, we recode the names of transportation modes into more general ones. Table A14 contains details on the mapping between the original and the synthetic names of transportation modes.

TABLE A14. Recoding mode of transportation names

Original name of transportation mode	Wide definition	Narrow definition
Container vessel	Vessel	
Inland vessels at sea vessel	Vessel	
Inland vessels	Vessel	
Marine vessel	Vessel	Vessel
Marine, river vessel that moves under its own power as a commodity	Vessel	
Railway wagon on sea vessel	Vessel	
Trailer or semi-trailer sea vessel	Vessel	
Truck on sea vessel	Vessel	
Posting using maritime transport	Vessel	
Automobile vehicle that moves under its own power as a commodity	Automobile	
Container on a truck	Automobile	
Posting using automobile transport	Automobile	
Truck	Automobile	Automobile
Container on a railway carriage	Railway	
Posting using railway transport	Railway	
Railway wagon	Railway	Railway
Trailer or semi-trailer on railway carriage	Railway	
Truck on a railway carriage	Railway	
Aircraft	Aircraft	Aircraft
Aircraft that moves under its own power as a commodity	Aircraft	
Posting using air transport	Aircraft	
Truck on the aircraft	Aircraft	
Container on the aircraft	Aircraft	
Express shipment	Other	
Mailing	Other	
Moving goods in hand luggage	Other	
Pipeline transportation	Other	
Power lines	Other	
The vehicle that moves under its own power as a commodity	Other	
Undefined	Not in sample	
Unknown	Not in sample	

C.2. Events around the Ports

In order to construct a series of military exposure of Black and Azov Sea ports, we collect events around the following ports:

- Port of Izmail
- Reni Commercial Seaport
- Ust-Danube Commercial Seaport
- Port of Kherson
- Port of Skadovsk
- Dnipro-Bug Commercial Seaport
- Mykolaiv Seaport
- Specialized Seaport Nika-Tera
- Specialized Seaport Olvia
- Bilhorod-Dnistrovskyi Seaport
- Port of Chornomorsk
- Port of Odesa
- Pivdennyi Port
- Port of Berdiansk
- Port of Mariupol
- Port of Kiliia
- Port Ochakiv
- Mykolaiv River Port

Appendix D. Additional Details on Transport Cost

These notes provide detailed analysis of the changes in transportation costs in Ukraine in 2022-2024 by different modes and validate our calculation of relative change in the transport cost between sea and land transport modes.

GOFI cross-validation. The International Grains Council (IGC) Grains and Oilseeds Freight Index (GOFI) Black Sea regional index is constructed from approximately 48 shipping routes linking two origin ports—Yuzhny in Ukraine and Novorossiysk in Russia—to approximately 19 destinations each, covering wheat and other heavy grains, maize, and barley. During the pre-war period, the index closely tracked the Odesa–Alexandria freight cost series, which we use as a proxy for Ukraine’s maritime transport costs (Figure 2). However, the two series diverge markedly after the Russian invasion in February 2022 (Figure D.1).

The Black Sea component accounts for 15.82% of the Global GOFI composite cost of maritime transport index, which also includes Brazil (30.32%), the United States (26.54%), Argentina (13.81%), Europe (6.50%), Canada (4.89%), and Australia (2.11%). Following the invasion, the GOFI Black Sea series remains broadly aligned with the six other regional components of the global index (Figure D.2). This suggests that the divergence of the Odesa–Alexandria series reflects Ukraine-specific shipping conditions rather than broader trends in global grain freight markets.

Multi-route USDA/CFTS comparison. Analysis of USDA/CFTS data - covering 17 routes across three crops, four ports, and five destinations - shows that the other routes from Ukrainian Black Sea ports track the Odesa-Alexandria benchmark closely in normal times. Per-route log-log elasticities range from 0.94 to 1.01 for short-haul Alexandria routes from Odesa and Mykolaiv (Table A15), while long-haul routes to China and Indonesia have log correlations of 0.62–0.73.

Figure D.3 shows freight rates for routes originating from the Ukrainian ports. Long-haul routes (China, Indonesia) command rates of 40-100 USD/mt and show a pronounced 2021-2022 spike, consistent with global dry bulk freight market tightness compounded by the Ukraine conflict. Short-haul routes to Alexandria and Turkey are substantially cheaper (15-40 USD/mt) and less volatile. Constanta (Romania) rates are notably low, reflecting Danube barge and short-sea shipping economics. Izmail rates carry a premium relative to Odesa, likely reflecting small vessel constraints and higher

per-tonne unit costs.

What factors explain variation and similarities in the maritime transportation cost indices? Regression analysis. Table A16 reports regressions of USDA/CFTS Table 9 sea freight rates on cargo characteristics, ports, destinations, and the Odesa – Alexandria benchmark. There is no statistically significant differences in the cost due to type of product, but significant variations across ports and destinations. At the same time, costs co-move responding to global trends in the shipping and logistic sectors. The estimated benchmark elasticity is 0.73, with significant heterogeneity across cargo types and destinations. The post-2022 interaction suggests a decline in benchmark sensitivity.

Cross-validation of transport costs from the literature. Two independent assessments of Ukrainian wartime transport costs allow direct comparison with the index-based findings above: Fernandes, Teixeira, and Santos (2023), a transport cost simulation, and the World Bank transport policy report on Ukraine’s logistics system published by Espitia et al. (2025).

The modal cost hierarchy in the simulation paper - sea cheapest, rail intermediate, road most expensive - is consistent with the indices estimated in our paper. The index-based finding that Ukraine road costs fell sharply post-invasion (to 56 by 2023Q1, 2021Q4 = 100) while sea spiked and then recovered maps well onto the simulation analysis: road-intensive chains are the most expensive alternatives and were effectively ruled out by market prices, while rail maintained a smaller premium. The simulation’s “best case” with smaller vessels corresponds to the initial period following Black Sea Grain Initiative (BSGI) reopening in mid-2022, when the sea/land ratio in Table 1 was 1.83 - confirming that sea costs were indeed elevated relative to the pre-war baseline.

The World Bank report uses observed grain shipping rates from the Ukraine Grain Association and Ukrzaliznytsia auction data to compute farm-to-destination costs for central Ukraine as of December 2024:

Route	Egypt	Spain	China
Odesa (Black Sea)	\$61/t	\$65/t	\$78/t
Danube ports (direct)	\$66/t	\$70/t	n/a
Danube → Constanta	\$68/t	\$72/t	\$85/t
Poland ports	\$125/t	\$108/t	\$142/t

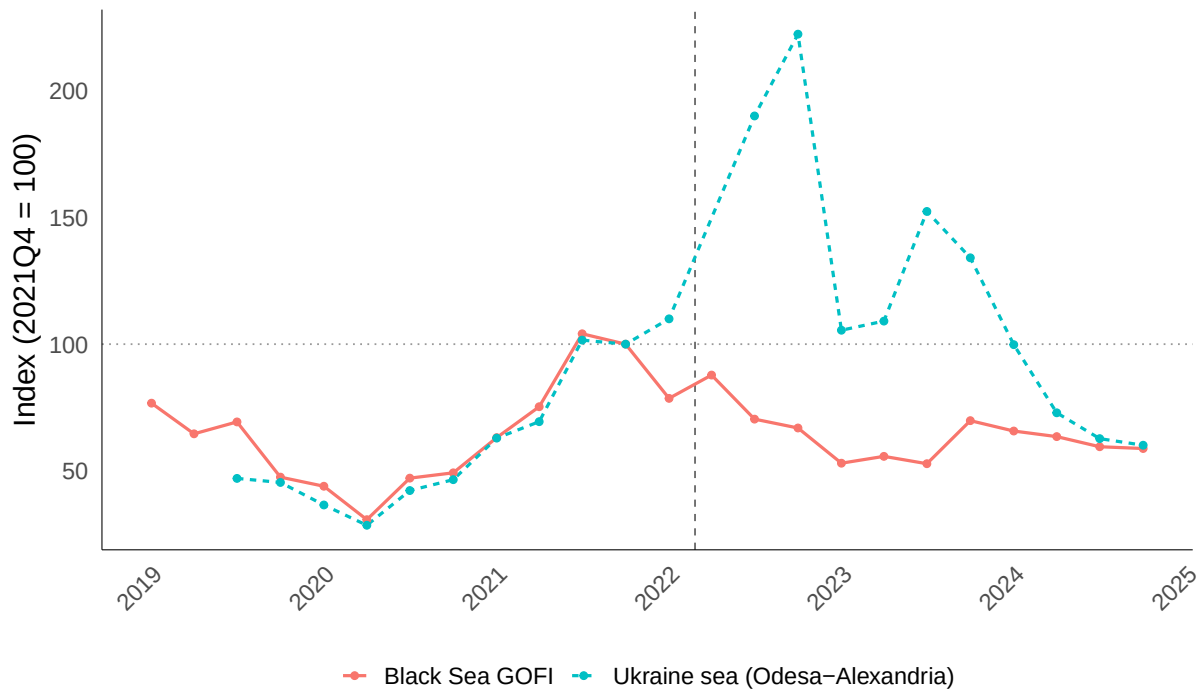
The Black Sea corridor’s dominance at end-2024 is unambiguous: Danube alterna-

tives cost only 8-11% more than Odesa, while Poland ports cost roughly double. This pattern directly validates the sea/land ratio of 0.77 in Table 1 (2024Q4): by end-2024, sea had become cheaper than the land average in index terms for the first time since before the war.

The World Bank's December 2024 snapshot aligns precisely with the final observation in this time series. The ratio crossing below 1.0 in 2024Q4 is consistent with the World Bank's finding that the new Black Sea corridor handled 76% of agricultural exports in 2024 and that ocean rates had by end-2024 reached pre-war levels. The World Bank additionally documents that Danube barge rates collapsed from a peak of \$50/t (August 2023) to \$10/t (December 2024) as Black Sea re-opening redirected grain flows from the Danube.

The European road freight index (Ti/Uppl/IRU benchmark) remained essentially flat at 100 - 104 throughout 2020-2024 - confirmed by the benchmark report, which shows Warsaw-Duisburg spot rates declining modestly in 2023-2024. This stability serves two functions. First, it establishes that cost movements in Ukrainian freight modes are not artefacts of global or European logistics conditions but wartime shocks. Second, the World Bank's finding that Poland-port routes cost twice the Odesa route is directly interpretable in this light: Polish routes are expensive because they involve truck-intensive hauls across border crossing points operating near capacity, not because European road freight itself is expensive.

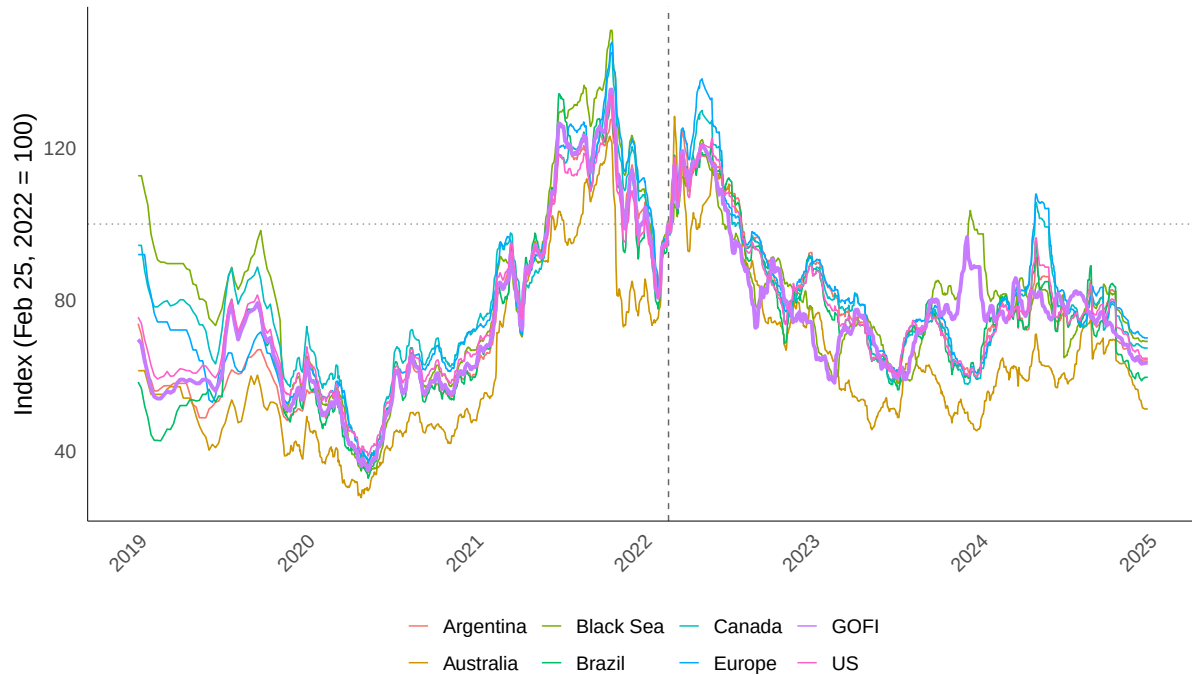
FIGURE D.1. GOFI Black Sea quarterly average vs Ukraine sea freight index (2021Q4 = 100).



Sources: IGC GOFI (Black Sea regional index, weekly, aggregated to quarters); IGC GOFI Odesa-Alexandria wheat rate (quarterly). Both series rebased to 2021Q4 = 100. Data through 2024Q4.

Note: “Ukraine sea” is the route-specific wheat rate (Odesa → Alexandria, 25,000-30,000 MT vessels). “Black Sea GOFI” is the IGC’s Black Sea regional freight index, constructed from routes originating at Ukraine’s Yuzhny port and Russia’s Novorossiysk to approximately 19 destinations each, covering wheat/heavy grains, maize, and barley.

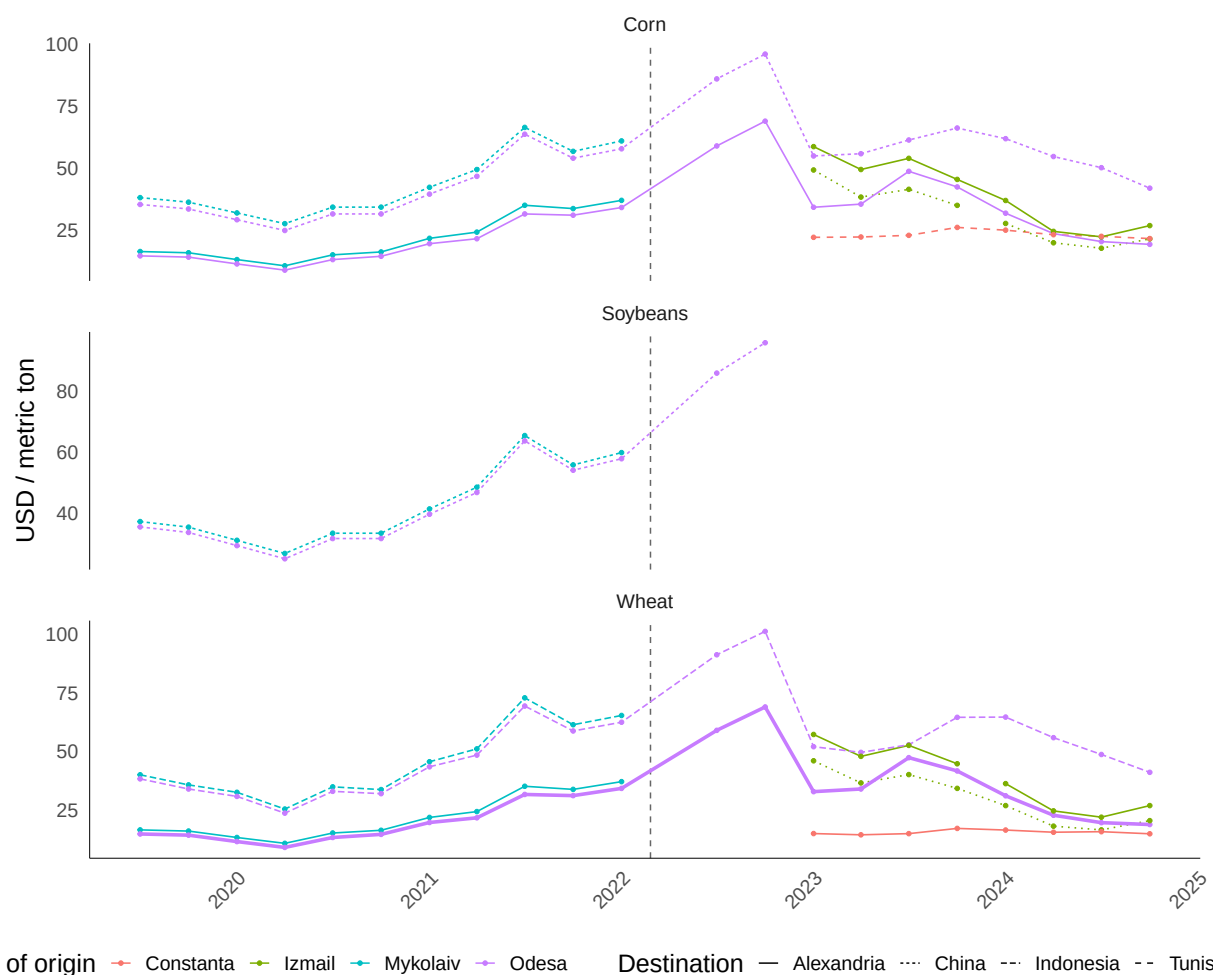
FIGURE D.2. IGC GOFI regional indices, all origins (Feb 25, 2022 = 100).



Source: International Grains Council, GOFI & Indices. Weekly frequency. All series rebased to the observation nearest February 25, 2022. Data restricted to 2019–2024.

Note: Seventeen isolated zero values in the Black Sea series (September 2023 - June 2024) replaced by linear interpolation. A value below 100 indicates that origin's freight costs declined relative to its own level at the invasion date. The overall IGC GOFI (thick line) is a global composite weighted across eight origins: Brazil 30.32%, US 26.54%, Argentina 13.81%, Black Sea 15.82%, Europe 6.50%, Canada 4.89%, Australia 2.11%. The Black Sea component covers routes from Ukraine (Yuzhny port) and Russia (Novorossiysk) to approximately 19 destinations each.

FIGURE D.3. USDA/CFTS Table 9 sea freight rates by crop and route (USD/mt).



Source: USDA Agricultural Marketing Service / Centre for Transport Strategies (CFTS), Kyiv. Table 9, quarterly, 2019Q1-2024Q4. Three panels by cargo type (Corn, Soybeans, Wheat). Colour = port of origin; line type = destination. Rates in USD per metric tonne.

Note: Mykolaiv routes end in 2022 following Russian occupation. Vessel sizes range from 3,000 to 70,000 MT across routes; larger vessels carry systematically lower per-tonne rates. Missing values (-na- in source data) excluded.

TABLE A15. Per-route correlation and log-log elasticity to Odesa-Alexandria wheat benchmark.

Cargo	Port	Destination	Vessel size	N	r	Elasticity	R^2
Corn	Constanta	Tunisia	25,000-30,000	8	0.46	0.09	0.22
Corn	Izmail	Alexandria	5,000-6,000	8	0.88	0.97	0.78
Corn	Izmail	Turkey	3000	4	0.83	0.69	0.70
Corn	Izmail	Turkey	60,000-70,000	4	-0.41	-0.34	0.17
Corn	Mykolaiv	Alexandria	25,000-30,000	11	1.00	0.95	1.00
Corn	Mykolaiv	China	50,000-55,000	11	0.99	0.63	0.97
Corn	Odesa	Alexandria	25,000-30,000	21	1.00	1.01	1.00
Corn	Odesa	China	60,000-70,000	21	0.97	0.63	0.94
Soybeans	Mykolaiv	China	60,000-70,000	11	0.99	0.65	0.97
Soybeans	Odesa	China	60,000-70,000	13	0.99	0.67	0.99
Wheat	Constanta	Alexandria	25,000-30,000	8	0.13	0.02	0.02
Wheat	Izmail	Alexandria	25,000-30,000	4	-0.26	-0.16	0.07
Wheat	Izmail	Alexandria	5,000-6,000	4	0.84	0.79	0.71
Wheat	Izmail	Turkey	5,000-6,000	8	0.86	0.98	0.74
Wheat	Mykolaiv	Alexandria	25,000-30,000	11	1.00	0.95	1.00
Wheat	Mykolaiv	Indonesia	50,000-55,000	11	0.98	0.73	0.97
Wheat	Odesa	Indonesia	50,000-55,000	21	0.94	0.62	0.88

Source: USDA/CFTS Table 9; see Figure D.3. Benchmark route: Wheat, Odesa → Alexandria, 25,000-30,000 MT. Correlations and log-log elasticities estimated by OLS on quarterly observations, 2019Q1-2024Q4.

Constanta wheat → Alexandria has near-zero correlation with the benchmark ($r = 0.13$), suggesting these routes respond to a distinct (Danube/Romanian) freight market.

Izmail 25-30k wheat → Alexandria has only 4 observations; estimates are unreliable.

Long-haul China/Indonesia elasticities (0.62-0.73) are lower than short-haul Alexandria ones (0.95-1.01), consistent with global bulk rates being partly driven by factors unrelated to the Black Sea corridor.

TABLE A16. Regression results: USDA/CFTS Table 9 sea freight rate determinants.

	(1) Level drivers	(2) Benchmark elasticity	(3) Heterogeneous elasticity	(4) Post-2022 break
Cargo: Corn	0.017 (0.018)	0.033 (0.019)	−0.535 (0.474)	
Cargo: Soybeans	0.006 (0.026)	0.018 (0.023)	−0.662 (0.476)	
Port: Mykolaiv	0.050* (0.021)	0.069*** (0.015)	0.067*** (0.011)	
Port: Izmail	0.390*** (0.070)	0.403*** (0.044)	0.317*** (0.051)	
Port: Constanta	−0.602*** (0.035)	−0.562*** (0.027)	−0.608*** (0.046)	
Dest: China	0.618*** (0.035)	0.634*** (0.021)	1.674*** (0.117)	
Dest: Indonesia	0.666*** (0.031)	0.696*** (0.019)	1.114* (0.502)	
Dest: Turkey	−0.263*** (0.040)	−0.262*** (0.032)	−0.172 (0.698)	
Dest: Tunisia	0.397*** (0.018)	0.380*** (0.019)	3.301*** (0.140)	
log(vessel)	0.096* (0.036)	0.080*** (0.016)	0.055* (0.025)	
log(bench)		0.725*** (0.064)		0.776*** (0.048)
log(bench) × Wheat			0.785*** (0.161)	
log(bench) × Corn			0.958*** (0.038)	
log(bench) × Soybeans			0.994*** (0.038)	
log(bench) × China			−0.330*** (0.037)	
log(bench) × Tunisia			−0.870*** (0.038)	
post2022				0.635· (0.334)
log(bench) × post2022				−0.182· (0.099)
Fixed effects: year, quarter	Yes	No	No	No
Fixed effects: route	No	No	No	Yes
Observations	200	179	179	179
R ²	0.886	0.931	0.953	0.937

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$.

Source: USDA/CFTS Table 9; see Figure D.3.

Dependent variable: log(rate_usd). Standard errors clustered at route level (in parentheses). Reference categories: Wheat (cargo), Odesa (port), Alexandria (destination).

Model (1): Level determinants with year and quarter fixed effects. Cargo type is statistically insignificant; port and destination effects are large and robust. Constanta routes cost 46% less than Odesa; Izmail 48% more. China and Indonesia routes cost 86% and 95% more than Alexandria routes.

Model (2): Common benchmark elasticity (0.725): a 10% rise in the Odesa–Alexandria rate is associated with a 7.3% rise across all routes on average.

Model (3): Heterogeneous elasticity: Corn and Soybeans track the benchmark more tightly (0.96–0.99) than Wheat (0.79). China routes are less elastic to the benchmark by 0.33 log points. Tunisia by 0.87 log points.

Model (4): Post-invasion interaction declines by −0.18: modest evidence of decoupling from the benchmark after February 2022, consistent with structural disruption and re-routing.