International Trade when Ports are Blocked

The Cost of Russia's Blockade of Ukrainian Ports

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Introduction

- Maritime trade dominates global transportation:
  - most cost-effective method for transporting large volumes over long distances
  - particularly critical for bulk commodity exports

- Maritime chokepoints are increasingly weaponised as instruments of economic coercion:
  - Russia's naval blockade of Ukraine (2022 – present)
  - Houthi attacks in the Red Sea (2023 – present)
  - Strait of Hormuz blockade (2026 – present)

- We study effects of Russia's blockade of Ukrainian seaports on Ukrainian international trade:
  - seaports were the primary gateway for Ukrainian exports
  - Russia's full-scale invasion severed key naval routes, severely disrupting trade logistics

- **This paper:**
  - *empirically:* shifts in trade patterns and transportation modes in response to the blockade
  - *quantitatively:* welfare cost of the port blockade using a quantitative trade model
  - *conceptually:* resilience of trade networks to maritime disruptions

The Blockade Evolved in Three Phases



- One of the key findings: meaningful recovery only after GC (military de-blockade), *not* after GD (BSGI) $\rightarrow$ the diplomatic solution delivered partial relief at best

Preview of Results

We proceed in four steps:

1. **Aggregate collapse**: Synthetic control shows that Ukraine's exports underperformed counterfactual by $\sim$50% in value
2. **Causal isolation of the maritime channel**: Shift-share DiD exploiting pre-war vessel dependence across product-destination pairs: trade flows dependent on ports underperformed and partially shifted to other modes
3. **Back-of-envelope attribution**: Blockade accounts for $\frac{1}{3}$ to $\frac{2}{3}$ of export decline; $\frac{1}{5}$ to $\frac{2}{5}$ of 2022 GDP contraction
4. **Quantitative Ricardian model** with discrete transport mode choice $\Rightarrow$ 4.1% welfare loss for Ukraine; up to 0.2% for low-income food importers

Data

Ukrainian Trade Data (TDM/ADF)

- Monthly, Jan 2017 – Sep 2025
- **10-digit HS product code**
- Source oblast (region of origin)
- Partner country
- Mode of transport: vessel, truck, rail, aircraft, other
- Value (USD) and quantity (kg)

Unit of observation:
product $\times$ destination $\times$ origin *spell*

Supplementary Data

- **Global TDM**: 118 countries for synthetic control
- **IMF PortWatch**: satellite port call data, 11 Ukrainian ports
- **VIINA 2.0** (Zhukov 2023): georeferenced conflict events, daily frequency
- **OECD ICIO 2021**: 80 countries, 50 sectors
- **CEPII Gravity**: bilateral distances

Related Literature

- **Trade Costs and Transport:** Anderson & Van Wincoop (2004); Hummels (2007); Coşar & Demir (2018); Donaldson (2018); Duranton, Morrow & Turner (2014); Fuchs & Wong (2026)
  - → We study effects of *port blockade-induced* increase in trade cost
- **Transport Mode Choice:** Hummels & Schaur (2013); Tolva (2026); Chowdhry, Heiland & Mahlkow (2026); Lugovskyy, Skiba & Terner (2025), Ko et al. (2026)
  - → We study *abrupt elimination* of the dominant mode, not marginal cost changes
- **Conflict, Sanctions & Supply-Chain Disruptions:** Martin, Mayer & Thoenig (2008); Chowdhry et al. (2024); Baldwin & Freeman (2022); Kuhla et al. (2023)
  - → We isolate the port channel from other war shocks
- **Quantitative Trade Models:** Eaton & Kortum (2002); Caliendo & Parro (2015); Hinz, Mahlkow & Wanner (2025)
  - → We add mode-specific elasticities estimated from detailed trade data
- **Contribution**: first causal identification and welfare quantification of a sustained maritime blockade

The Aggregate Trade Collapse

Ukraine's Exports Underperformed Their Counterfactual by 50%

- Method: Synthetic control (Abadie & Gardeazabal 2003) - construct a "synthetic Ukraine" from donor countries that replicates the pre-war trade trajectory
- Pre-war fit: close across value and quantity, exports and imports
- After Feb 2022: sharp, *persistent* divergence

More Results

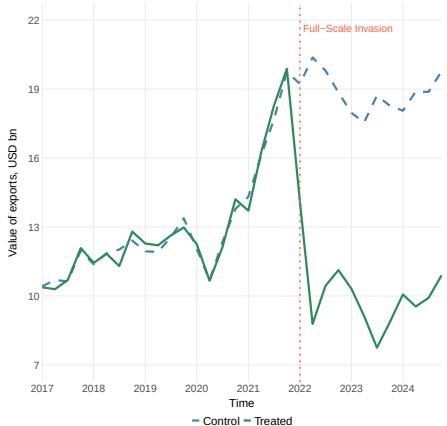


Figure: Exports Value

Synthetic Difference-in-Differences

	Middle income pool		Agri and metal pool	
	Aggregate flow (1)	Bilateral flow (2)	Aggregate flow (3)	Bilateral flow (4)
Export quantity				
Coefficient	-0.495	-1.955***	-0.459	-1.665***
(s.e.)	(0.507)	(0.186)	(0.399)	(0.0897)
Change in %	-39.04	-85.84	-36.81	-81.08
Export value				
Coefficient	-0.748**	-1.591***	-0.621***	-1.447***
(s.e.)	(0.255)	(0.157)	(0.109)	(0.0657)
Change in %	-52.67	-79.63	-46.26	-76.47
Import quantity				
Coefficient	-1.094***	-0.660***	-0.999*	-0.423**
(s.e.)	(0.281)	(0.136)	(0.423)	(0.142)
Change in %	-66.51	-48.31	-63.18	-34.49
Import value				
Coefficient	-0.365*	-0.438**	-0.323***	-0.289**
(s.e.)	(0.173)	(0.139)	(0.0495)	(0.0944)
Change in %	-30.58	-35.47	-27.60	-25.10
N	1,728	171,072	384	38,016

Two Patterns Point to the Maritime Channel

Pattern 1: Bilateral $\gg$ Aggregate

Distant, lower-volume partners relied almost entirely on sea. Trade with nearby European partners (accessible by road/rail) proved more resilient.

Pattern 2: Exports $\gg$ Imports

Blockade directly targeted outbound Black Sea routes. Import logistics were more diversified pre-war — suppliers could reroute via Romanian or Polish borders.

Both patterns suggest the maritime channel as the dominant driver.

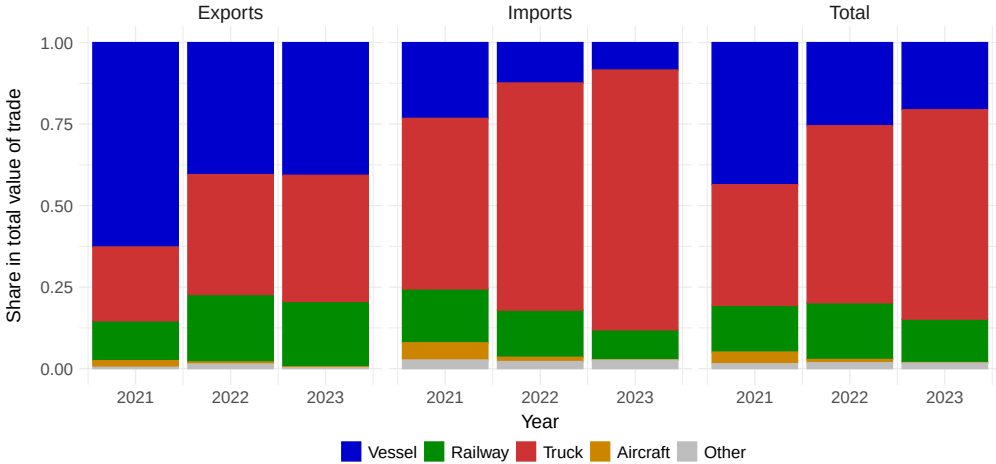
Why Did Trade Decline?

- Decline in production:
  - Labor: forced displacement and military service
  - Capital: damaged facilities, lower investment, blocked imports of capital equipment
  - Decline in usable agricultural land; infrastructure destruction
- Changes in consumption, saving, and credit markets
- Destruction of road and rail infrastructure
- Blockade of trade routes:
  - **Maritime transport** ← **this paper**
  - Air transport (airspace closed from day 1)

Our approach:

- isolate the decline in trade due to the port blockade using causal inference
- the shift-share design exploiting pre-war variation in vessel dependence across product-destination-origin spells

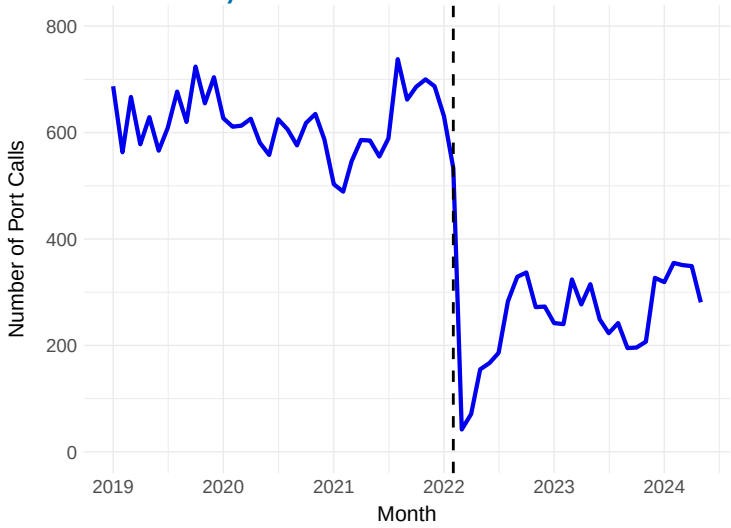
Ukraine's Trade by Mode of Transportation



Source: Data from the State Statistical Service of Ukraine

Exports by destination | Imports by destination | Exposure of Exports by Region | Exposure of Export by Product

Port Blockade and Activity in Ukrainian Ports



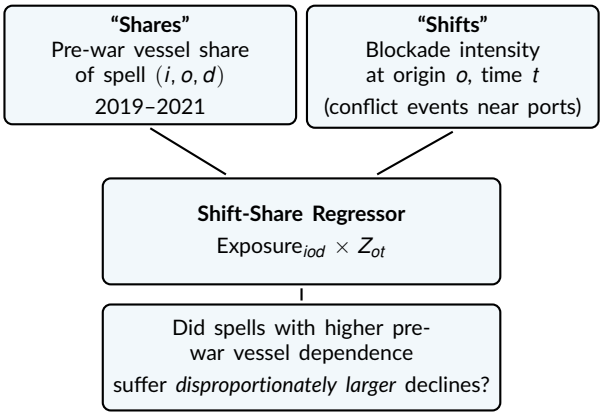
Source: Data from Portwatch by the IMF

Calls by Ports

Identification Strategy

Identification: The Core Idea

We examine: common shocks of port blockade on specific outcomes for trade spells with a heterogeneous level of exposure to this shock



- Precondition: shift-share instrument is orthogonal to the error component in the outcome variable
  - Goldsmith-Pinkham et al. (2020): for shares to serve as a valid exogenous shock, they only need to be uncorrelated with the *change* in the outcome variable
  - Borusyak et al. (2021): if one assumes the exogeneity of common shocks, concerns over the endogeneity of shares could be overlooked
- Identification does *not* require maritime exposure to be randomly assigned → after absorbing α_{it}, α_{ot}, α_{dt}, α_{iod}, pre-war vessel dependence is uncorrelated with *differential* changes in outcomes

The “Shares”: Pre-War Maritime Exposure

Definition: for spell (i, o, d),

$$\text{Exposure}_{iod} = \frac{\sum_{\tau \in 2019\text{–}21} Y^{\text{vessel}}_{iod\tau}}{\sum_{\tau \in 2019\text{–}21} Y^{\text{total}}_{iod\tau}}$$

- Quantity- or value- based
- Also used as binary: any maritime use in 2019-21

Properties:

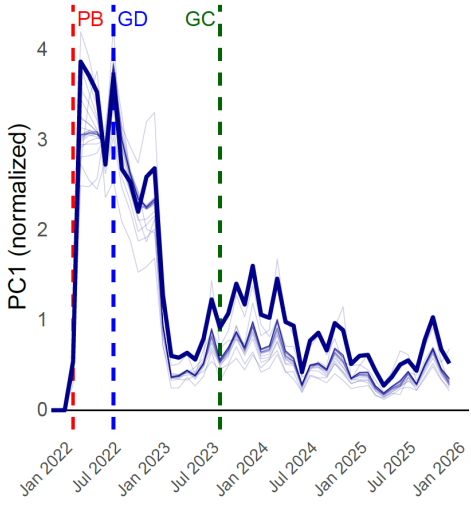
- Exposure measured from 2019–2021, before full-scale invasion
- Varies by *product-destination-origin region* triplet
- Absorbed by spell FE α_{iod}: no time-varying confound from product or geography

The “Shifts”: Blockade Intensity from Conflict Events

1. Geolocate 18 Ukrainian maritime ports
2. Record all VIINA 2.0 conflict events within **10 km radius** daily: airstrikes, UAV/artillery hits, air alerts, fires, property damage
3. Extract **first principal component** $\Rightarrow$ single blockade intensity index g_{pt}
4. Aggregate to oblast level via inverse-distance weights:

$$Z_{ot} = \sum_{p} \theta^{e}_{op} \cdot g_{pt}$$

- **Key validation:** spikes at Feb 2022; declines in two steps at GD and GC
- Main effect Z_{ot} absorbed by origin$\times$time FE. Only the *interaction* with pre-war exposure identifies the channel.



Main Empirical Specification

$$Y_{iodt} = \alpha_{iod} + \alpha_{it} + \alpha_{ot} + \alpha_{dt} + \beta \underbrace{\text{Exposure}_{iod}}_{\text{pre-war vessel share}} \times \underbrace{\text{Shift}_{ot}}_{\text{blockade intensity}} + \varepsilon_{iodt}$$

Outcomes and Estimators

Outcomes Y_{iodt}:

- quantity, value
- unit value (price)
- extensive margin dummy

Estimators: OLS (intensive margin), Poisson PPML (handles zeros), Logit (extensive margin)

FEs and SEs

Fixed effects absorb:

- α_{iod}: time-invariant trade costs, distance, quality
- α_{it}: product seasonality, commodity price cycles
- α_{ot}: all oblast-level war shocks (destruction, displacement, energy)
- α_{dt}: foreign demand and policy shocks

SE: clustered at destination-origin pairs

β: relative performance of port-vs. land-routed spells, post- vs. pre-blockade.

Relative Performance of Export Spells: Binary Shock

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Shift (binary)	-0.2769***	-0.5969**	-0.2194***	-0.7122***	0.0575**	-0.1833***
	(0.0551)	(0.2637)	(0.0548)	(0.1403)	(0.0248)	(0.0622)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,611,750	6,065,962	1,611,750	6,065,962	1,611,750	5,989,851
R^2	0.89246	0.90321	0.77957	0.81594	0.94623	0.45783

Robustness: Exposure by value · Robustness: Exposure if any vessel · Robustness: Unrestricted sample
Robustness: Dropping regions affected by war since 2014 · Robustness: Additionally dropping regions affected by war since 2022 the most

Relative Performance of Export Spells: Event-Study

- Event-study to identify pre-trends and anticipation effects:

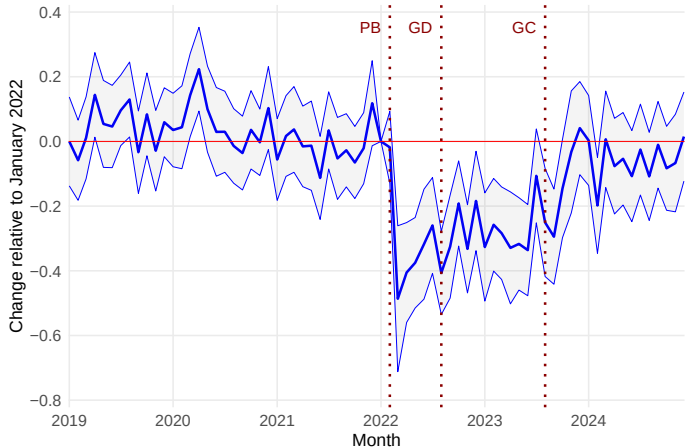
$$\log Y_{iodt} = \alpha_{iod} + \alpha_{im} + \alpha_{ot} + \alpha_{dt} + \sum_{\substack{\tau=Jan19 \\ t \neq Jan22}}^{Oct24} \beta_\tau \mathbb{1}\{t = \tau\} \times \text{Exposure}_{iod} + \varepsilon_{iodt},$$

where:

- Y_{iodt}: Export outcome (value, quantity, unit value) for an export spell
- $Exposure_{iod}$: Exposure to maritime transportation (quantity, unit, unit value), average in 2019-2021
- $\mathbb{1}\{t = \tau\}\times$ - indicator function equal to 1 when $t = \tau$
- α_{iod}, α_{im}, α_{ot}, α_{dt} - fixed effects

Relative Quantity of Exports: Event-Study

Exposure by a share of maritime transportation in total quantity, average for 2019-2021



Note: 90% confidence bands

Relative Performance of Export Spells: Many Shocks

Exposure by a share of maritime transportation in total quantity, average for 2019-2021
Shift: Distance-weighted events in 10 km radius around the ports, 1st principal component, normalized

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Shift (continuous)	-0.4153***	-1.480***	-0.3341***	-1.823***	0.0812**	-0.3288***
	(0.0761)	(0.3554)	(0.0804)	(0.1989)	(0.0322)	(0.0965)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,611,750	6,065,962	1,611,750	6,065,962	1,611,750	5,989,851
R^2	0.89244	0.90348	0.77955	0.81651	0.94623	0.45783

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Relative Performance of Export Spells: Further Results

- More detailed timeline:
  - the biggest rebound since establishing the Grain Corridor (after 01.08.2023) Details
  - no significant effect of blockade of the western border (Nov 2023 - Apr 2024) Details
  - event-study confirms the most significant rebound since military de-blockade of naval routes Details
- Non-linear exposure
  - quantity and value decrease and prices increase stronger for more exposed export spells
  - less dependent flows are more likely to be destroyed Details
- Heterogeneity by products
  - worse performance of products traditionally shipped through ports (e.g, bulky goods, or agricultural) Details 1 Details 2
  - highly-exposed agricultural goods dropped sharper and rebounded faster Event-Study
- Heterogeneity by destination
  - stronger negative effects for longer distances Details
- Heterogeneity by origin
  - relative underperformance in regions less dependent on ports Details
- Heterogeneity by exposure to war
  - limited role in explaining the relative performance Details

Switching between Transportation Modes: Baseline Result

Exposure by a share of maritime transportation in total value, average for 2019-2021

Dependent Variables:	Share of ...			Quantity with ...			Probability of ...		
	Vessel	Truck	Railway	Vessel	Truck	Railway	Vessel	Truck	Railway
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	Poisson	Poisson	Poisson	Logit	Logit	Logit
Variables									
Exposure × Shift (binary)	-0.6000***	0.2562***	0.0480***	-1.744*	2.528***	1.865***	-2.454***	2.634***	4.220***
	(0.0136)	(0.0281)	(0.0057)	(0.9991)	(0.2001)	(0.4268)	(0.1136)	(0.1192)	(0.5373)
Fixed-effects									
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	1,656,042	1,656,042	1,656,042	2,142,066	7,590,371	151,413	2,141,631	7,543,206	150,594
R^2	0.87526	0.86850	0.79710	0.8968	0.8718	0.9378	0.2314	0.3203	0.2732

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Switching between Transportation Modes: Further Results

- More detailed timeline
  - switching to trucks was longer-lived, recovery of vessels share since the Grain Corridor Details
- Non-linear exposure
  - stronger switching for export spells more dependednt on ports pre-war Details
- Heterogeneity by products
  - homogeneous goods mostly switched to trucks, intermediate goods - to both trucks and railway Details Shares Details Logit
  - active switching for goods traditionally shipped through ports (agriculture and minerals) Details Shares Details Logit
- Heterogeneity by destination
  - higher relocation to trucks on short distances, no particular pattern for railway Details Shares
- Heterogeneity by origin
  - easier switch to other modes in regions less dependent on ports Details Logit Details Shares
- Heterogeneity by exposure to war
  - more exposure to war increases probability of switching to land transport Details Logit
  - more exposure to war reduces the extent of switching to trucks Details Shares

Relative Performance of Import Spells: Binary Shock

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		CIF Price	Import (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Shift (binary)	-0.1683***	-0.6576***	-0.0560*	-0.1772***	0.1123***	0.0510
	(0.0402)	(0.1283)	(0.0331)	(0.0580)	(0.0161)	(0.0459)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	5,463,667	14,701,893	5,463,667	14,701,893	5,463,667	14,137,193
R^2	0.79666	0.93565	0.68153	0.85033	0.86001	0.50401

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Relative Performance of Import Spells: Many Shocks

Exposure by a share of maritime transportation in total quantity, average for 2019-2021 Shift: Distance-weighted events in 10 km radius around the ports, 1st principal component, normalized

Dependent Variables:	Quantity		Value		CIF Price	Import (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Shift (continuous)	-0.2320***	-0.3976*	-0.0339	-0.1841*	0.1981***	0.0655
	(0.0502)	(0.2154)	(0.0446)	(0.1005)	(0.0222)	(0.0671)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	5,463,667	14,701,893	5,463,667	14,701,893	5,463,667	14,137,193
R^2	0.79665	0.93563	0.68152	0.85039	0.86000	0.50401

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Back-of-the-Envelope Calculations

Contribution of Blockade

- How much did the port blockade contribute to export decline?

$$c_X = \frac{\omega \times |\hat{\beta}|}{\Delta X}$$

where $\omega = 0.626$ (pre-war maritime share in export value), $|\hat{\beta}|$ relative reduction for fully exposed spells, $\Delta X = 0.527$ (total export value decline from SDID)
OLS: $c_X \approx$ **33%** Poisson: $c_X \approx$ **71%** $\Rightarrow$ central estimate $\frac{1}{3}$ to $\frac{2}{3}$

- How much did the port blockade contribute to GDP contraction?

$$c_Y = c_X \times \frac{\psi \times \Delta X}{\Delta Y}$$

where $\psi = 0.341$ (goods exports share of GDP in 2021), $\Delta Y = 0.311$ (real GDP decline in 2022)
OLS: $c_Y \approx$ **19%** Poisson: $c_Y \approx$ **41%** $\Rightarrow$ central estimate $\frac{1}{5}$ to $\frac{2}{5}$

- But: no GE effects here $\rightarrow$ missing intercept problem

Quantitative Model

Model: International Trade with Transport Modes

- Ricardian multi-country multi-sector trade model à la **Caliendo & Parro (2015)** extended with **discrete choice over transport modes** à la **Tolva (2026)**

Full model details

- $N = 80$ countries, $J = 49$ sectors (27 tradable), calibrated to **OECD ICIO 2021**
- Effective iceberg cost on route (d, o) in sector l aggregates M modes via CES:

$$\tau_{do}^{l} = \left[\sum_{m=1}^{M} \left(\tau_{do}^{l,m} \right)^{1-\eta^{l}} \right]^{\frac{1}{1-\eta^{l}}}, \qquad \eta^{l} > 1$$

  η^{l} = elasticity of substitution across modes in sector l

- Pass-through of blockade shock $\hat{\tau}_{do}^{l,s}$ to vessel mode s, holding other modes fixed (eq. C.11):

$$\hat{\tau}_{do}^{l} = \left[1 + \left(\hat{\tau}_{do}^{l,s} \right)^{1-\eta^{l}} \pi_{do}^{l,s} \right]^{\frac{1}{1-\eta^{l}}}$$

- **Key implication:**
  - pass-through depends only on the pre-shock sea share $\pi_{do}^{l,s}$ and η^{l}
  - substitution *always attenuates* the shock (weakest for high sea share and low η^{l})

Model: Aggregate Elasticity of Substitution between Transport Modes

Dependent Variable:	$arcsinh(Q^{maritime}) - arcsinh(Q^{land})$	
Trade Flow:	Exports	Imports
Model:	(1)	(2)
Variables		
Share × Shift	-1.692***	-1.499***
	(0.209)	(0.216)
Fixed-effects		
Product×Destination×Origin	✓	✓
Product×Period	✓	✓
Destination×Period	✓	✓
Origin×Period	✓	✓
Fit statistics		
Observations	7,069,437	15,150,726
R^2	0.48745	0.47821

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Share: 1 if any maritime transportation used in 2019–2021
Shift: distance-weighted events within 10 km, 1st PC, rescaled to match relative cost change

- Follow approach by Ryzhenkov & Shepotylo (2026)
- From the CES modal share equation:

$$\log \frac{q_{iod}^{l,\text{vessel}}}{q_{iod}^{l,\text{land}}} = -\eta^{l} \log \frac{\tau_{iod}^{l,\text{vessel}}}{\tau_{iod}^{l,\text{land}}}$$

  Identify $-\eta^{l}$ directly from the log quantity ratio.
- $\hat{\eta}^{X} = \mathbf{1.69}$, $\hat{\eta}^{M} = \mathbf{1.50}$
- Consistent with Tolva (2026): range 1.5-2.5
- Sectoral elasticities range between 1.07-5.05
  Sectoral Elasticities
- Consistent with Ko, Nigai, and Truax (2025): up to 11
- Sector-specific estimates feed directly into the model

Model: Calibration

Data inputs:

- **OECD ICIO 2021**: 80 countries, 49 sectors - IO coefficients $\{\gamma_{o'}^{k,l}\}$, value-added shares $\{\beta_o^l\}$, consumption shares $\{\alpha_d^l\}$
- **BACI from CEPII**, 2021: bilateral trade shares $\{\pi_{do}^l\}$
- **Tariffs**: MAcMap-HS6 by Guimbard et al. (2012)
- **Trade elasticities** $\{\theta^l\}$: Fontagné, Guimbard, and Orefice (2022)
- **Modal substitution elasticities** $\{\eta^l\}$: estimated from Ukrainian trade data
- **Maritime exposure shares** $\pi_{do}^{l,s}$: TDM data, pre-war vessel share by sector $\times$ destination, averaged 2019-2021
- Implemented in **KITE** package Hinz, Mahlkow, and Wanner (2025)
- Hat algebra requires only baseline trade shares, IO coefficients, and elasticities - no unobserved productivity levels needed Dekle, Eaton, and Kortum (2007)

Welfare Results

Model: Headline Effects

Indicator	Blockade only	No RU/BL only	Both
Panel A: Welfare			
Welfare (real income)	−4.07	−1.47	−5.65
Real wage	−3.83	−1.40	−5.32
Nominal income	−6.49	−1.18	−7.83
Panel B: Trade			
Exports	−30.22	−11.81	−41.77
Imports	−28.93	−11.33	−40.11
Panel C: Prices and production			
Nominal wage	−6.25	−1.11	−7.51
Consumer price index	−2.52	+0.30	−2.31
Total production (real)	−5.81	−1.96	−7.43

Reference: $\tau = 2$ on all UA trade $\rightarrow \Delta$ welfare $= -12.9\%$

Scenarios:

- **S1. Blockade only:** closure of Ukrainian ports and Black Sea routes ($\tau = 2.14$)
- **S2. RUS/BLR only:** Ukraine halts all trade with Russia and Belarus
- **S3. Both:** blockade combined with the RUS/BLR halt

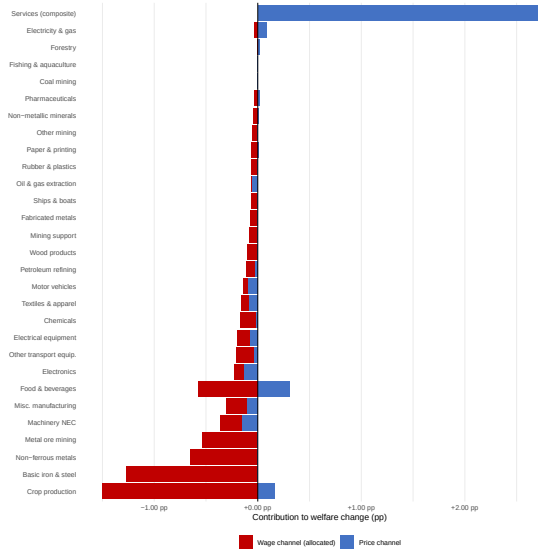
Takeaways:

- The blockade alone causes a 4.1% welfare loss and a 5.8% contraction in real production
- Halting trade with Russia and Belarus adds a further 1.6% welfare loss

Welfare decomposition:

- Wage channel dominates, but price channel provides partial offset

Model: Sectoral Contributions to Welfare

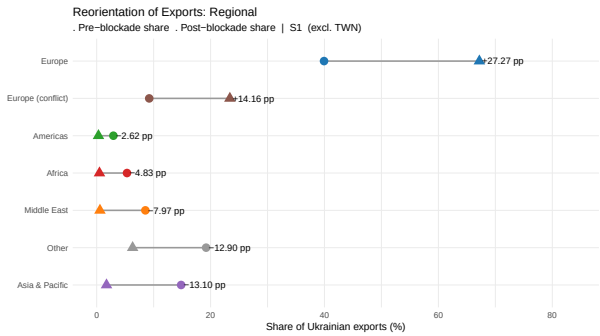


- **Agriculture**: largest single contributor - most exposed sector
- **Basic metals & metal ores**: second-largest wage-channel loss
- **Food & beverages**: strong wage loss, partially offset by positive price channel
- **Services**: act as a buffer / absorber

Contributions for S3

Sectoral Effects

Model: Reorientation of Exports



Reorientation by Regions in S3

Best/Worst Performers

Trade vs. Cost by Country

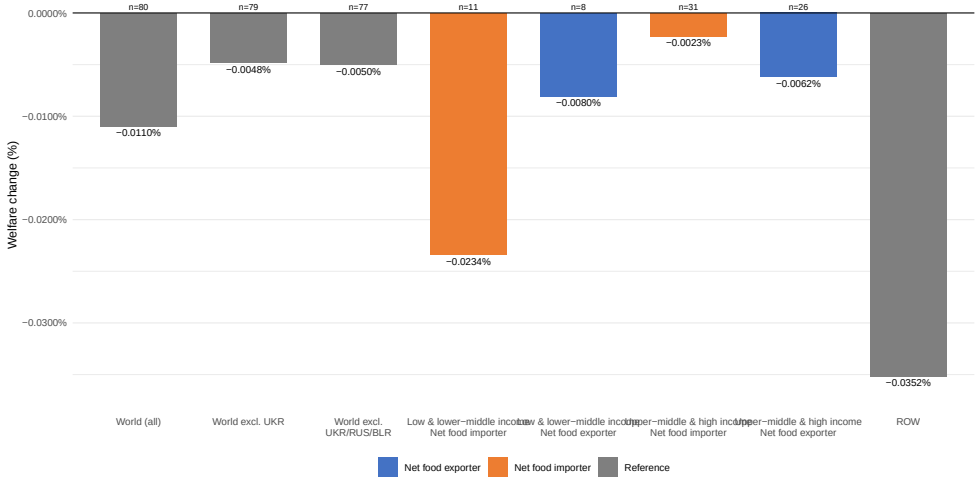
Trade vs. Cost by Country-Sector

- Blockade triggers sharp reorientation toward European partners reachable overland
- Vessel-dependent routes hit hardest
- Non-European destinations: disproportionate losses
- Elasticity of bilateral flow to mode-specific shock:

$$\frac{\partial \ln X_{do}^{l}}{\partial \ln \tau_{do}^{l,s}} = -\theta^{l} \pi_{do}^{l,s} (1 - \pi_{do}^{l})$$

$\rightarrow$ Sea-intensive routes respond most strongly

Welfare Cost for the World



Group means weighted by baseline value added. Income groups: World Bank classification. ROW is a composite and carries no income group. Excluded from every aggregate: UKR, RUS, BLR, TWN.

Unweighted Scenario S3

Welfare Cost for the World

- Third-country effects are small in aggregate (-0.005% excl. UA/RU/BL) but highly unequal
- Low- and lower-middle-income net food importers: -0.023%, about $5\times$ the world average
- Worst affected country: -0.19%, about $40\times$ the world average
- Mechanism: less Ukrainian grain and oil $\Rightarrow$ higher food prices for importers $\Rightarrow$ higher food bills
- Net food exporters in the same income group lose less (-0.008%): higher food prices partly offset their loss
- Upper-middle- and high-income countries: close to zero on average
- Quantitative foundation for the food-security concerns behind the BSGI

All Countries

Model: Sensitivity to η and τ^{Sea}

	Relative sea cost τ^{Sea}				
Elasticity ($\hat{\eta}_X$, $\hat{\eta}_M$)	1.50	2.14	3.00	5.00	10.00
No substitution (0, 0)	−4.99	−5.93	−6.36	−6.75	−7.17
Cobb-Douglas (1, 1)	−4.90	−5.76	−6.11	−6.36	−6.55
Uniform (1.10, 1.10)	−4.89	−5.74	−6.09	−6.33	−6.50
Narrow modes (1.51, 2.23)	−4.74	−5.46	−5.72	−5.87	−5.95
Wide, binary (1.69, 1.50)	−4.84	**−5.65**	−5.96	−6.18	−6.31
Wide, continuous (2.29, 2.50)	−4.75	−5.47	−5.74	−5.90	−5.98
Uniform (5.00, 5.00)	−4.52	−5.02	−5.15	−5.19	−5.20

- The S3 result holds in every cell: Ukraine loses 4.5–7.2% of welfare
- Even a high elasticity cannot offset the blockade: with $\eta = 5$ the loss is still 5.0%
- Substitution matters more when the sea-cost shock is larger: the gap low and high $\eta 0$ grows with τ^M

Model: Policy Counterfactuals

	Scenario	Welfare change (%)	Δ vs S3 (pp)
Blockade			
S1	Blockade only	−4.07	–
S2	RUS/BLR severance only	−1.47	–
S3	Both	−5.65	–
Policy, applied on top of S3			
S4	BSGI ceiling	−4.76	+0.89
S5	Land corridor (half shock)	−5.53	+0.12
S6	Land corridor (shock removed)	−4.98	+0.66
S7	BSGI + Land corridor	−4.34	+1.30

- Land corridor mitigates the loss, but only if its penalty is removed in full
- Partial restoration of sea freight (BSGI) has a stronger effect
- The two policies work best together, but less than the sum of their separate effects
- Only full restoration of maritime access recovers most of the loss

Conclusions

- Russia's blockade was a large, persistent, and causally identifiable shock
  - Aggregate exports underperformed their synthetic counterfactual by $\sim$50%
  - Shift-share design isolates the maritime channel from the war's many other shocks
  - Blockade alone explains $\frac{1}{3}$ to $\frac{2}{3}$ of the export decline, $\frac{1}{5}$ to $\frac{2}{5}$ of 2022's GDP contraction

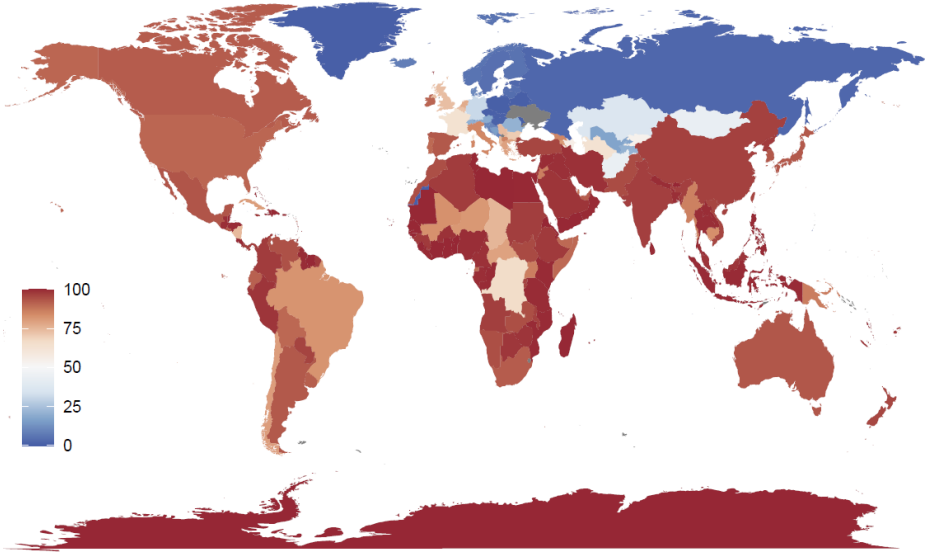
- The structural model confirms this range and prices the welfare cost
  - 4.1% welfare loss, 5.8% contraction in real production for Ukraine from the blockade alone
  - Halting RUS/BLR trade adds a further 1.6 p.p.
  - Modal substitution *cushions* the shock but never eliminates it

- Spillovers abroad are small on average but concentrated on the most vulnerable
  - Low- and lower-middle-income net food importers lose up to 40$\times$ the world average

- Policy helps, but only partly closes the gap
  - Grain corridor: +0.9 p.p.
  - Land corridor: +0.7 p.p.
  - Restoring maritime access itself rather than diplomatic workarounds is what actually recovers most of the loss

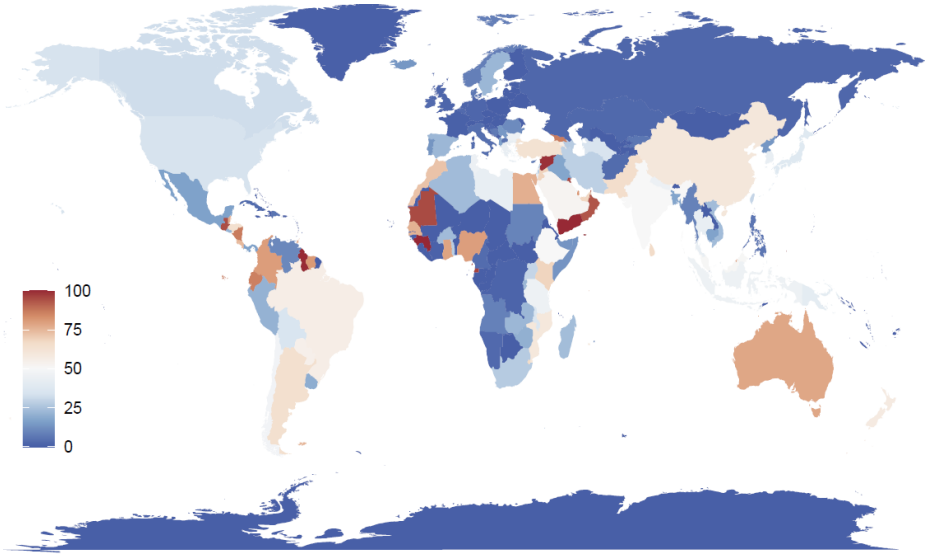
Additional Slides

Maritime Transportation in Exports Value by Destination in 2021, %



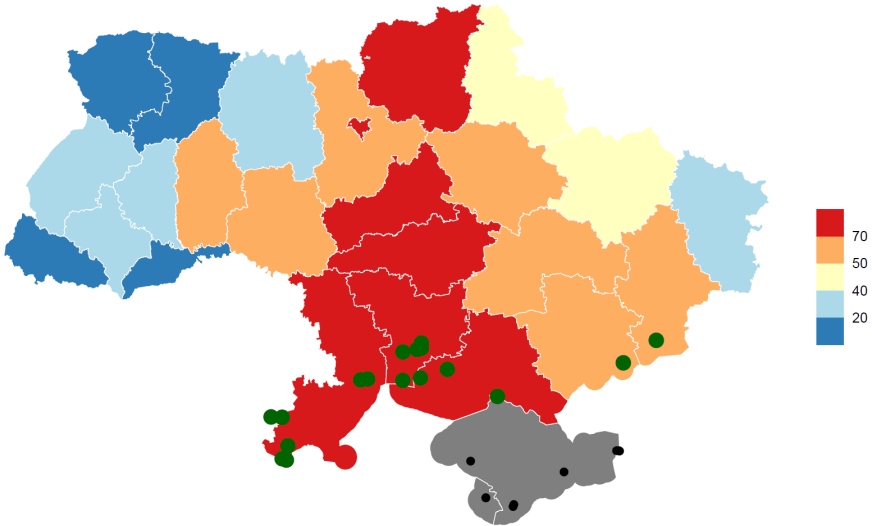
Back

Maritime Transportation in Imports Value in 2021 by Destination, %



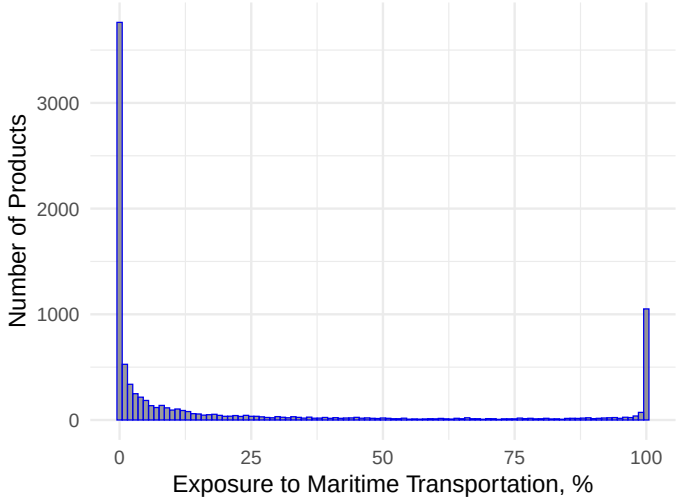
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Maritime Transportation in Exports Value in 2021 by Oblast, %



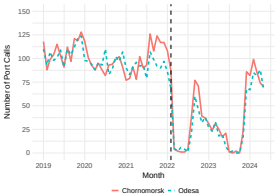
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Maritime Transportation in Exports Value in 2021 by Product, %

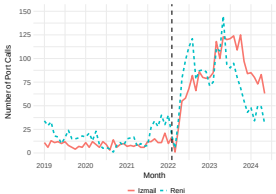


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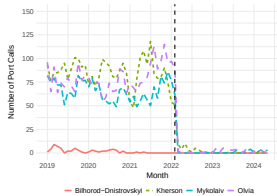
Calls by Different Ports



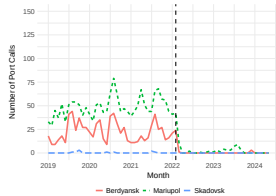
(a) Rebounded



(b) Increased



(c) Blocked



(d) Occupied

Source: Data from Portwatch by the IMF

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Synthetic Control: Additional Results



Figure: Exports Quantity

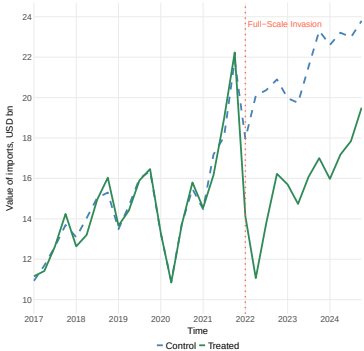


Figure: Imports Value

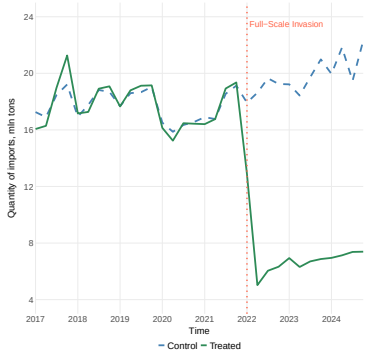


Figure: Imports Quantity

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Relative Performance of Export Spells

Exposure by a share of maritime transportation in total value, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Port Blockade	-0.2973***	-0.7482**	-0.1517***	-0.8361***	0.1456***	-0.1452**
	(0.0507)	(0.3227)	(0.0543)	(0.1480)	(0.0343)	(0.0723)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	10,758,795	1,655,304	10,758,795	1,655,304	10,705,517
R^2	0.8804	0.9189	0.8017	0.8774	0.9023	0.3192

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells

Exposure if any shipments with vessels in 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Port Blockade	-0.2289***	-0.8571***	-0.1336***	-0.6399***	0.0953***	-0.2110***
	(0.0358)	(0.1935)	(0.0319)	(0.1001)	(0.0188)	(0.0578)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	10,758,795	1,655,304	10,758,795	1,655,304	10,705,517
R^2	0.8804	0.9190	0.8017	0.8773	0.9023	0.3193

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Unrestricted Sample

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Port Blockade	-0.2775***	-0.7257**	-0.1717***	-0.8099***	0.1058***	-0.1342*
	(0.0524)	(0.3219)	(0.0482)	(0.1476)	(0.0251)	(0.0698)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,711,169	11,486,807	1,711,169	11,486,807	1,711,169	11,432,310
R^2	0.8821	0.919118	0.8054	0.8774	0.9029	0.3177

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Drop 4 Oblasts

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Port Blockade	-0.2616***	-0.7418**	-0.1524***	-0.8297***	0.1092***	-0.1204
	(0.0552)	(0.3377)	(0.0505)	(0.1565)	(0.0268)	(0.0733)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,551,228	9,755,972	1,551,228	9,755,972	1,551,228	9,703,023
R^2	0.8778	0.9208	0.7975	0.8796	0.9002	0.3144

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Drop 8 Oblasts

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × Port Blockade	-0.2860***	-0.7504**	-0.1591***	-0.8815***	0.1270***	-0.1997**
	(0.0638)	(0.3696)	(0.0593)	(0.1804)	(0.0266)	(0.0882)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,195,388	7,054,817	1,195,388	7,054,817	1,195,388	7,005,271
R^2	0.8813	0.9284	0.7984	0.8883	0.9045	0.3095

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Model Equation for Export Dynamics: Detailed Timeline

- We study the relative aggregate export dynamics with maritime transport:

$$\begin{aligned}\log Y_{iodt} = {} & \alpha_{iod} + \alpha_{im} + \alpha_{ot} + \alpha_{dt} + \varepsilon_{iodt} \\ & + \beta_1 \text{Exposure}_{iod} \times \text{Port Blockade}_t \\ & + \beta_2 \text{Exposure}_{iod} \times \text{Port Blockade}_t \times \text{Grain Deal}_t \\ & + \beta_3 \text{Exposure}_{iod} \times \text{Port Blockade}_t \times \text{Grain Deal}_t \times \text{Grain Corridor}_t,\end{aligned}$$

where:

- Y_{iodt}: Export outcome (value, quantity, unit value) for an export spell
- $Exposure_{iod}$: Exposure to maritime transportation, average in 2019-2021
- $Post\ Blockade_t$: Indicator for post-blockade period (1 if $t \geq$ Feb-22)
- $Grain\ Deal_t$: Indicator for a period since UA-TR-RU grain deal (1 if $t \geq$ Aug-22)
- $Grain\ Corridor_t$: Indicator for a period since a grain corridor (1 if $t \geq$ Aug-23)
- $\alpha_{iod}, \alpha_{im}, \alpha_{ot}, \alpha_{dt}$ - fixed effects

Relative Performance of Export Spells: Detailed Timeline

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × PB	-0.2277***	-1.461***	-0.1546***	-1.527***	0.0731***	-0.1537**
	(0.0503)	(0.2414)	(0.0503)	(0.1442)	(0.0229)	(0.0740)
Exposure × PB × GD	-0.1127**	0.5627*	-0.0850*	0.4597***	0.0277	-0.0592
	(0.0507)	(0.3295)	(0.0437)	(0.1643)	(0.0252)	(0.0631)
Exposure × PB × GD × GC	0.1147**	0.4915*	0.1327***	0.6902***	0.0179	0.1346**
	(0.0516)	(0.2609)	(0.0422)	(0.1277)	(0.0252)	(0.0600)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	10,758,795	1,655,304	10,758,795	1,655,304	10,705,517
R^2	0.8804	0.9189	0.8017	0.8776	0.9023	0.3192

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Role of Border Blockade

Exposure by a share of maritime transportation in total quantity, average for 2019-2021
Blockade of Western Border: between November 2023 and April 2024

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure × PB	-0.2277***	-1.458***	-0.1546***	-1.526***	0.0731***	-0.1537**
	(0.0503)	(0.2417)	(0.0504)	(0.1444)	(0.0229)	(0.0740)
Exposure × PB × GD	-0.1127**	0.5630*	-0.0849*	0.4598***	0.0277	-0.0592
	(0.0507)	(0.3307)	(0.0437)	(0.1645)	(0.0252)	(0.0631)
Exposure × PB × GD × GC	0.0993**	0.3058	0.1267***	0.6299***	0.0274	0.1300**
	(0.0503)	(0.3288)	(0.0421)	(0.1629)	(0.0277)	(0.0596)
Exposure × PB × GD × GC × Border Block	0.0444	0.5431	0.0171	0.1713	-0.0273	0.0133
	(0.0502)	(0.3319)	(0.0444)	(0.2386)	(0.0306)	(0.0394)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	10,758,795	1,655,304	10,758,795	1,655,304	10,705,517
R^2	0.8804	0.9189	0.8017	0.8776	0.9023	0.3192

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Event-Study

- Event-study to identify pre-trends and anticipation effects:

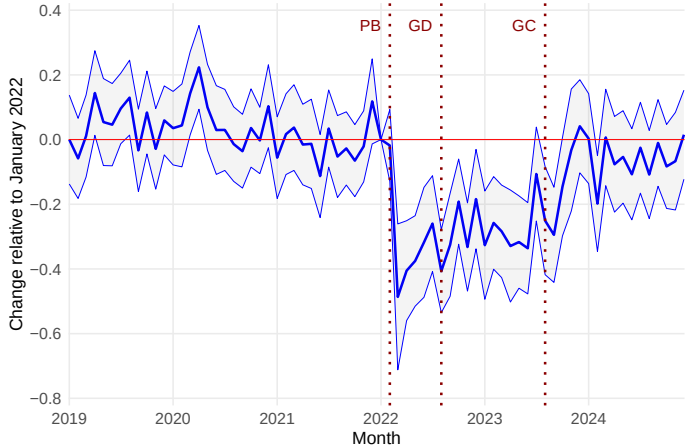
$$\log Y_{iodt} = \alpha_{iod} + \alpha_{im} + \alpha_{ot} + \alpha_{dt} + \sum_{\substack{\tau=Jan19 \\ t \neq Jan22}}^{Oct24} \beta_\tau \mathbb{1}\{t = \tau\} \times \text{Exposure}_{iod} + \varepsilon_{iodt},$$

where:

- Y_{iodt}: Export outcome (value, quantity, unit value) for an export spell
- $Exposure_{iod}$: Exposure to maritime transportation (quantity, unit, unit value), average in 2019-2021
- $\mathbb{1}\{t = \tau\}\times$ - indicator function equal to 1 when $t = \tau$
- α_{iod}, α_{im}, α_{ot}, α_{dt} - fixed effects

Relative Quantity of Exports: Event-Study

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

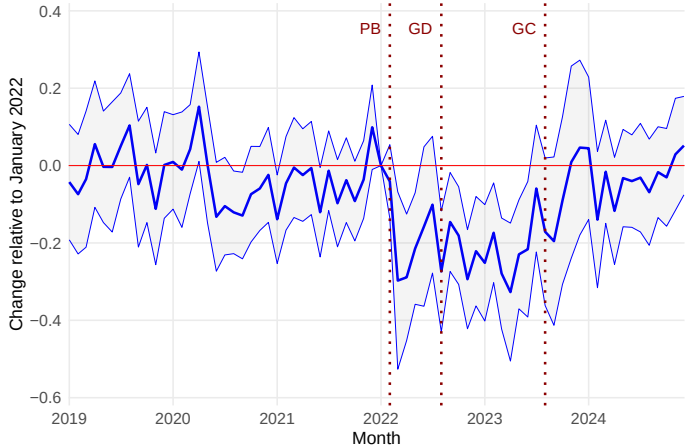


Note: 90% confidence bands

Back Value FOB Price

Relative Value of Exports: Event-Study

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

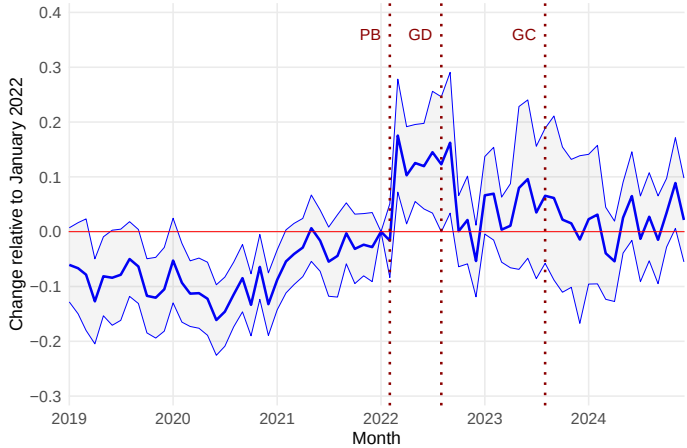


Note: 90% confidence bands

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Relative Export Prices: Event-Study

Exposure by a share of maritime transportation in total quantity, average for 2019-2021



Note: 90% confidence bands

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Relative Performance of Export Spells: Non-Linear Exposure

- We extend the baseline regression specification as

$$\begin{aligned}\log Y_{iodt} =& \alpha_i + \alpha_{it} + \alpha_{ot} + \alpha_{dt} + \alpha_{op} + \varepsilon_{iodt} \\ &+ \beta^h \mathbb{1}\{\text{Exposure}_{iod} > 0.5\} \times \text{Post Blockade}_t \\ &+ \beta^l \mathbb{1}\{\text{Exposure}_{iod} \leq 0.5\} \times \text{Post Blockade}_t,\end{aligned}$$

where:

- Y_{iodt}: Export outcome (value, quantity, unit value) for an export spell
- $\{\text{Exposure}_{iod} > 0.5\}$: more than 50% of quantity (value) shipped through ports in 2019-2021
- $\{\text{Exposure}_{iod} \leq 0.5\}$: more than 0% but less than 50% of quantity (value) shipped through ports in 2019-2021
- *Post Blockade*$_t$: Indicator for post-blockade period (1 if $t \geq$ Feb-22)
- α_{iod}, α_{im}, α_{ot}, α_{dt} - fixed effects

Relative Performance of Export Spells: Non-Linear Exposure

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity		Value		FOB Price	Export (0/1)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Method:	OLS	Poisson	OLS	Poisson	OLS	Logit
Variables						
Exposure Low × Port Blockade	-0.1824***	-0.8214***	-0.0976***	-0.4200***	0.0847***	-0.2613***
	(0.0387)	(0.1602)	(0.0309)	(0.0922)	(0.0214)	(0.0691)
Exposure High × Port Blockade	-0.2838***	-0.9077***	-0.1763***	-0.8113***	0.1075***	-0.1808***
	(0.0487)	(0.3230)	(0.0462)	(0.1370)	(0.0241)	(0.0650)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	10,758,795	1,655,304	10,758,795	1,655,304	10,705,517
R^2	0.8804	0.9190	0.8017	0.8774	0.9022	0.3193

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Heterogeneity by Products

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity					
Products:	All	Homogeneous	Intermediate	All	Homogeneous	Intermediate
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	Poisson	Poisson	Poisson
Variables						
Exposure × Port Blockade	-0.2670***	-0.3716***	-0.4063***	-0.7280**	-0.5552	-0.6941*
	(0.0533)	(0.1086)	(0.0643)	(0.3231)	(0.4278)	(0.3938)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	381,824	811,880	10,758,795	2,301,931	5,372,573
R^2	0.8804	0.9270	0.9042	0.9189	0.9008	0.9143

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Heterogeneity by Products

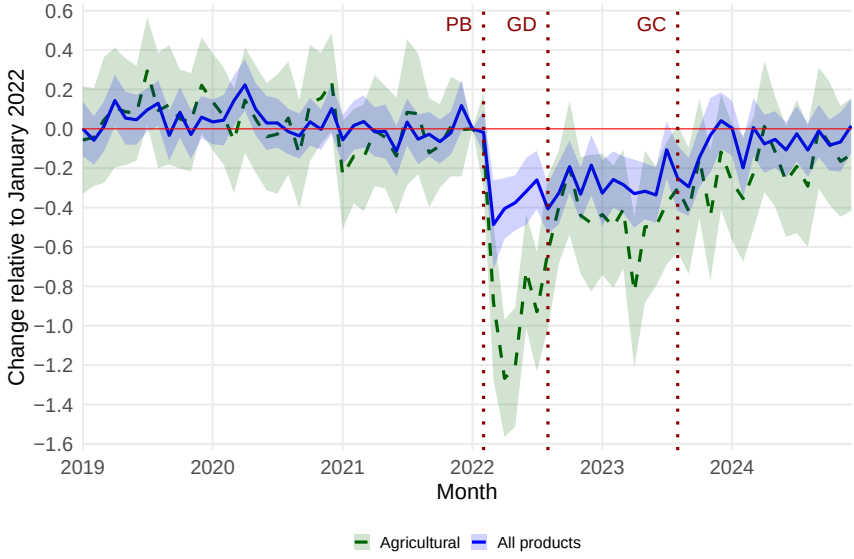
Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity							
Products:	All	Agriculture	Minerals	Metals	All	Agriculture	Minerals	Metals
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson
Variables								
Exposure × Port Blockade	-0.2670***	-0.5823***	-0.7140*	-0.1947	-0.7280**	-1.210***	0.3278	-1.250***
	(0.0533)	(0.1084)	(0.4289)	(0.1387)	(0.3231)	(0.2270)	(1.106)	(0.2796)
Fixed-effects								
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	1,655,304	179,533	26,851	230,498	10,758,795	1,180,432	121,694	1,423,387
R^2	0.8804	0.9152	0.9043	0.8398	0.9189	0.8641	0.9655	0.9346

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Event Study: Relative Performance of All vs. Agricultural Products



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Relative Performance of Export Spells: Distance to Destination

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity							
Distance to Destination:	All	$\leq$ 1500 km	1500-5000 km	$>$ 5000 km	All	$\leq$ 1500 km	1500-5000 km	$>$ 5000 km
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson
Variables								
Exposure $\times$ Port Blockade	-0.2670***	-0.2397**	-0.2262***	-0.8025***	-0.7280**	-0.5954	-1.160***	-1.662*
	(0.0533)	(0.1005)	(0.0776)	(0.2363)	(0.3231)	(0.3822)	(0.3955)	(0.9639)
Fixed-effects								
Product$\times$Destination$\times$Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	1,655,304	1,147,037	377,226	131,041	10,758,795	5,841,585	2,701,162	873,682
R^2	0.8804	0.8631	0.8945	0.9098	0.9189	0.9448	0.8848	0.9631

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Heterogeneity by Origin

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity					
Exposure to Ports:	All	$\leq$ 50% value	$>$ 50% value	All	$\leq$ 50% value	$>$ 50% value
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	Poisson	Poisson	Poisson
Variables						
Exposure $\times$ Port Blockade	-0.2670***	-0.3132**	-0.2218***	-0.7280**	-0.8420***	-0.7480*
	(0.0533)	(0.1273)	(0.0596)	(0.3231)	(0.2367)	(0.3924)
Fixed-effects						
Product$\times$Destination$\times$Origin	✓	✓	✓	✓	✓	✓
Product$\times$Period	✓	✓	✓	✓	✓	✓
Destination$\times$Period	✓	✓	✓	✓	✓	✓
Origin$\times$Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	520,239	1,135,065	10,758,795	2,677,664	7,438,944
R^2	0.8804	0.8618	0.8864	0.91887	0.89763	0.92282

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Relative Performance of Export Spells: Role of Exposure to War

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Quantity									
Model:	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) Poisson	(7) Poisson	(8) Poisson	(9) Poisson	(10) Poisson
Variables										
Exposure × PB	-0.2670***	-0.2636***	-0.2634***	-0.2714***	-0.2696***	-0.7280**	-0.6399*	-0.7489**	-0.6754**	-0.7617**
	(0.0533)	(0.0546)	(0.0536)	(0.0535)	(0.0543)	(0.3231)	(0.3471)	(0.3260)	(0.3392)	(0.3228)
Exposure × PB × Property		-0.0036					-0.0886			
		(0.0138)					(0.0638)			
Exposure × PB × War Fire			-0.0143					0.0493		
			(0.0089)					(0.0487)		
Exposure × PB × Air Alert				0.0066					-0.0775	
				(0.0143)					(0.0526)	
Exposure × PB × Occupied					0.0712					0.9711
					(0.1112)					(0.7262)
Fixed-effects										
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics										
Observations	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	10,758,795	10,758,795	10,758,795	10,758,795	10,758,795
R^2	0.8804	0.8804	0.8804	0.8804	0.8804	0.9189	0.9189	0.9189	0.9189	0.9189

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Detailed Timeline

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of ...			Quantity with ...			Probability of ...		
	Vessel	Truck	Railway	Vessel	Truck	Railway	Vessel	Truck	Railway
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	Poisson	Poisson	Poisson	Logit	Logit	Logit
Variables									
Exposure × PB	-0.4859***	0.1967***	0.0644***	-1.962***	1.702***	0.7445	-2.097***	2.479***	3.640***
	(0.0150)	(0.0274)	(0.0061)	(0.6741)	(0.2347)	(0.7249)	(0.1292)	(0.1175)	(0.5727)
Exposure × PB × GD	-0.1540***	0.0796***	-0.0129**	0.5439	0.6245***	0.9822	-0.2429	0.1386*	0.6055
	(0.0144)	(0.0151)	(0.0061)	(0.4357)	(0.1609)	(0.6387)	(0.1683)	(0.0735)	(0.4905)
Exposure × PB × GD × GC	0.0278**	-0.0132	-0.0122***	-0.4177	0.6789***	0.8773**	-0.3550**	0.0801	0.4188
	(0.0108)	(0.0101)	(0.0042)	(0.6969)	(0.1361)	(0.4316)	(0.1735)	(0.0492)	(0.4393)
Fixed-effects									
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	1,656,042	1,656,042	1,656,042	2,142,066	7,590,371	151,413	2,141,631	7,543,206	150,594
R^2	0.87548	0.86854	0.7971	0.896835	0.872152	0.938015	0.231415	0.32028	0.273274

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Non-Linear Exposure

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of ...			Quantity with ...			Probability of ...		
	Vessel	Truck	Railway	Vessel	Truck	Railway	Vessel	Truck	Railway
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	Poisson	Poisson	Poisson	Logit	Logit	Logit
Variables									
Exposure Low × Port Blockade	-0.1143***	0.0040	0.0028	-8.534***	-0.0070	-0.9018***	-6.677***	-0.1958**	-0.4611
	(0.0123)	(0.0152)	(0.0051)	(0.9552)	(0.0742)	(0.2069)	(0.3610)	(0.0947)	(0.3821)
Exposure High × Port Blockade	-0.5343***	0.2251***	0.0384***	-8.399***	2.030***	1.765***	-7.585***	1.882***	3.019***
	(0.0120)	(0.0220)	(0.0056)	(0.7548)	(0.1632)	(0.4160)	(0.3532)	(0.0967)	(0.5221)
Fixed-effects									
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	1,656,042	1,656,042	1,656,042	2,142,066	7,590,371	151,413	2,141,631	7,543,206	150,594
R^2	0.87387	0.86853	0.79698	0.8970	0.8716	0.9388	0.2357	0.3199	0.2727

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Products

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of Trucks			Share of Railways		
Products:	All	Homogeneous	Intermediate	All	Homogeneous	Intermediate
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Exposure × Port Blockade	0.2563***	0.3739***	0.2561***	0.0481***	0.1127***	0.0834***
	(0.0281)	(0.0244)	(0.0263)	(0.0057)	(0.0140)	(0.0102)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	381,824	811,880	1,655,304	381,824	811,880
R^2	0.8695	0.9125	0.8781	0.7971	0.8323	0.8374

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Products

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:		Truck (0/1)			Railway (0/1)	
Products:	All	Homogeneous	Intermediate	All	Homogeneous	Intermediate
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Exposure × Port Blockade	2.634***	3.452***	2.321***	4.220***	4.538***	13.65***
	(0.1192)	(0.1657)	(0.1320)	(0.5373)	(0.6192)	(2.073)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	7,543,206	1,218,897	3,815,542	150,594	106,139	37,824
R^2	0.3203	0.2863	0.3113	0.2732	0.2928	0.2191

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Products

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of Trucks				Share of Railway			
Products:	All	Agricultural	Minerals	Metals	All	Agricultural	Minerals	Metals
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Exposure × Port Blockade	0.2563***	0.4271***	0.2949***	0.1727***	0.0481***	0.1497***	0.1623***	0.0681***
	(0.0281)	(0.0228)	(0.0749)	(0.0349)	(0.0057)	(0.0182)	(0.0506)	(0.0194)
Fixed-effects								
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	1,655,304	179,533	26,851	230,498	1,655,304	179,533	26,851	230,498
R^2	0.86946	0.91944	0.92816	0.86973	0.79712	0.69105	0.93911	0.86469

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Products

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Truck (0/1)				Railway (0/1)			
Products:	All	Agricultural	Minerals	Metals	All	Agricultural	Minerals	Metals
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Exposure × Port_Block	2.634***	3.352***	4.308***	1.895***	4.220***	4.379***	11.39***	4.650***
	(0.1192)	(0.2401)	(0.6002)	(0.1675)	(0.5373)	(1.045)	(3.034)	(1.476)
Fixed-effects								
Product-Destination-Origin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-Period	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-Period	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-Period	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	7,543,206	506,882	56,535	1,046,822	150,594	34,295	17,835	29,207
R^2	0.3203	0.2631	0.1918	0.3264	0.2732	0.1627	0.2537	0.2561

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Distance to Destination

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of Trucks				Share of Railway			
Distance to Destination:	All	$\leq$ 1500 km	1500-5000 km	$>$ 5000 km	All	$\leq$ 1500 km	1500-5000 km	$>$ 5000 km
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Exposure $\times$ Port Blockade	0.2563***	0.4461***	0.3728***	0.0211	0.0481***	0.0414***	0.0490***	0.0329***
	(0.0281)	(0.0377)	(0.0303)	(0.0283)	(0.0057)	(0.0111)	(0.0081)	(0.0117)
Fixed-effects								
Product$\times$Destination$\times$Origin	✓	✓	✓	✓	✓	✓	✓	✓
Product$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Destination$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Origin$\times$Period	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	1,655,304	1,147,037	377,226	131,041	1,655,304	1,147,037	377,226	131,041
R^2	0.8695	0.8335	0.8819	0.9175	0.7971	0.8752	0.7535	0.7324

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Origin

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of Trucks			Share of Railway		
Model:	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Variables						
Exposure × Port Blockade	0.2563***	0.4048***	0.2396***	0.0481***	0.0439***	0.0517***
	(0.0281)	(0.0529)	(0.0310)	(0.0057)	(0.0159)	(0.0066)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	1,655,304	520,239	1,135,065	1,655,304	520,239	1,135,065
R^2	0.8695	0.8847	0.8741	0.7971	0.8053	0.8093

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Heterogeneity by Origin

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Truck (0/1)			Railway (0/1)		
Model:	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
Variables						
Exposure × Port Blockade	2.634***	3.128***	2.577***	4.220***	8.405***	5.037***
	(0.1192)	(0.2572)	(0.1329)	(0.5373)	(1.598)	(0.6794)
Fixed-effects						
Product×Destination×Origin	✓	✓	✓	✓	✓	✓
Product×Period	✓	✓	✓	✓	✓	✓
Destination×Period	✓	✓	✓	✓	✓	✓
Origin×Period	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	7,543,206	2,148,619	4,859,941	150,594	22,460	112,504
R^2	0.3203	0.2952	0.3087	0.2732	0.1887	0.2593

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Role of Exposure to War

Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:	Share of Trucks					Share of Railway				
Model:	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) OLS	(10) OLS
Variables										
Exposure × Port_Block	0.2563***	0.2725***	0.2578***	0.2647***	0.2595***	0.0481***	0.0439***	0.0483***	0.0442***	0.0479***
	(0.0281)	(0.0278)	(0.0284)	(0.0276)	(0.0285)	(0.0057)	(0.0053)	(0.0056)	(0.0054)	(0.0055)
Exposure × PB × Property		-0.0173**					0.0044*			
		(0.0069)					(0.0024)			
Exposure × PB × War Fire			-0.0062*					-0.0012		
			(0.0037)					(0.0014)		
Exposure × PB × Air Alert				-0.0126**					0.0057***	
				(0.0058)					(0.0020)	
Exposure × PB × Occupied					-0.0879					0.0027
					(0.0584)					(0.0381)
Fixed-effects										
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Fit statistics										
Observations	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304	1,655,304
R^2	0.8695	0.8695	0.8695	0.8695	0.8695	0.7971	0.7971	0.7971	0.7972	0.7971

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Switching between Transportation Modes: Role of Exposure to War

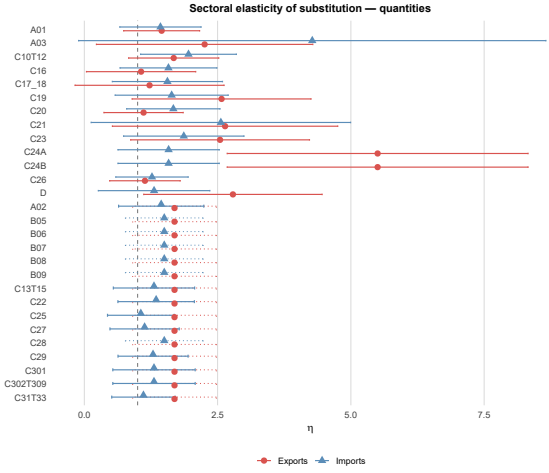
Exposure by a share of maritime transportation in total quantity, average for 2019-2021

Dependent Variables:			Truck (0/1)				Railway (0/1)			
Model:	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson	(7) Poisson	(8) Poisson	(9) Poisson	(10) Poisson
Variables										
Exposure × PB	0.0402***	0.0342***	0.0396***	0.0377***	0.0350***	0.0073***	0.0050***	0.0069***	0.0064***	0.0053***
	(0.0047)	(0.0056)	(0.0048)	(0.0050)	(0.0054)	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0008)
Exposure × PB × Property		0.0052***					0.0020***			
		(0.0012)					(0.0005)			
Exposure × PB × War Fire			0.0014**					0.0008***		
			(0.0007)					(0.0002)		
Exposure × PB × Air Alert				0.0030***					0.0011***	
				(0.0008)					(0.0003)	
Exposure × PB × Occupied					0.0585***					0.0215***
					(0.0156)					(0.0059)
Fixed-effects										
Product×Destination×Origin	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Product×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Destination×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Origin×Period	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Fit statistics										
Observations	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200	12,337,200
R^2	0.42009	0.42011	0.42009	0.42010	0.42015	0.38076	0.38086	0.38079	0.38080	0.38101

Clustered (Destination-Origin) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

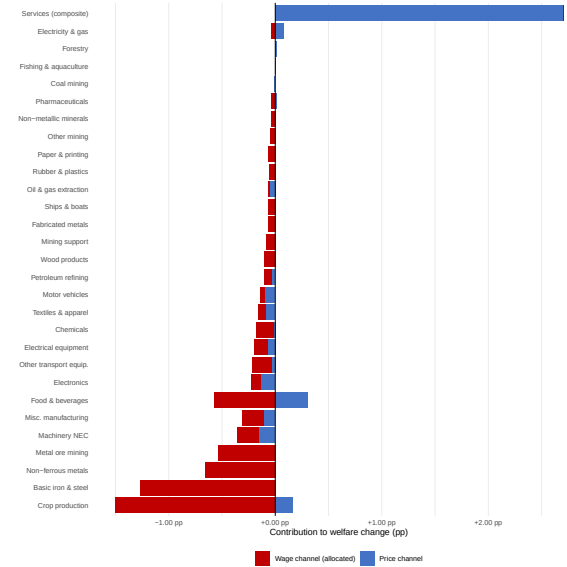
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Model: Sectoral Elasticity of Substitution between Transport Modes



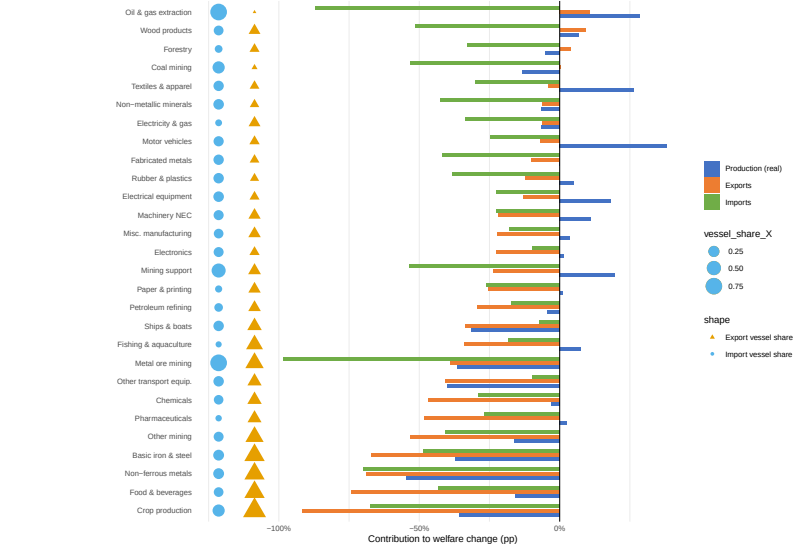
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Model: Sectoral Contributions to Welfare (Blockade + No RU/BL)



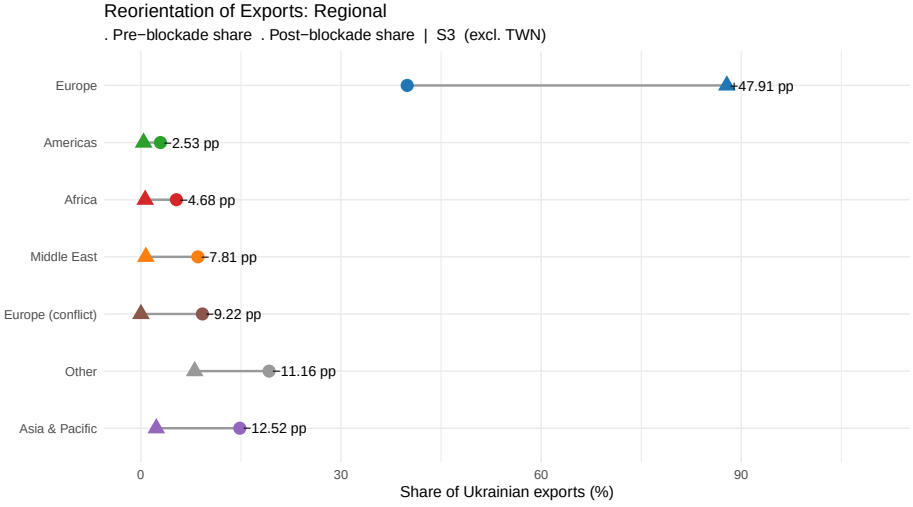
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Model: Sectoral Production and Trade (Blockade Only)



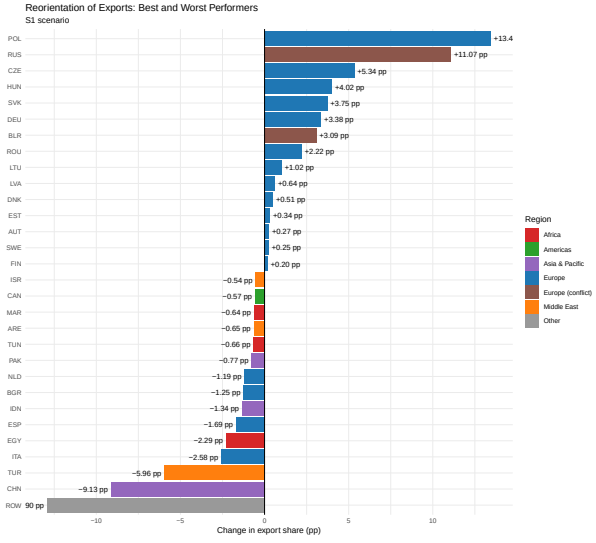
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Model: Reorientation of Exports



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Model: Reorientation of Exports by Countries



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Model: Bilateral Exports vs. Transport Cost Changes

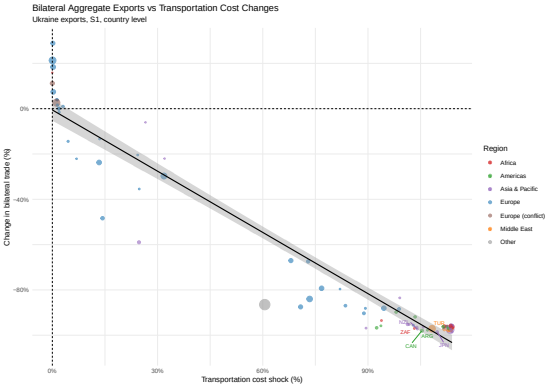


Figure: Exports

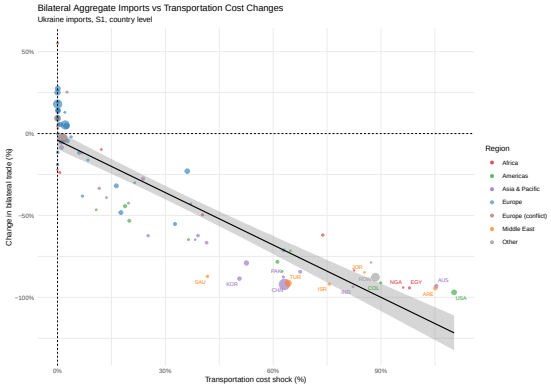


Figure: Imports

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Model: Bilateral Sectoral Exports vs. Transport Cost Changes

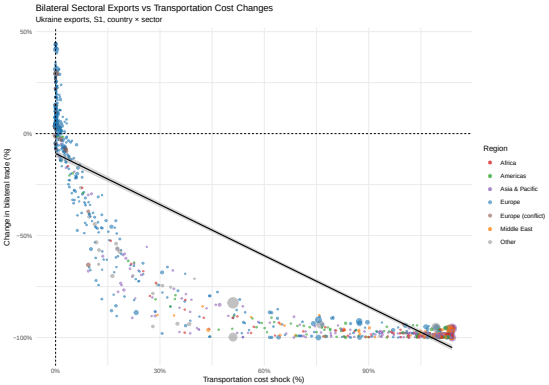


Figure: Exports

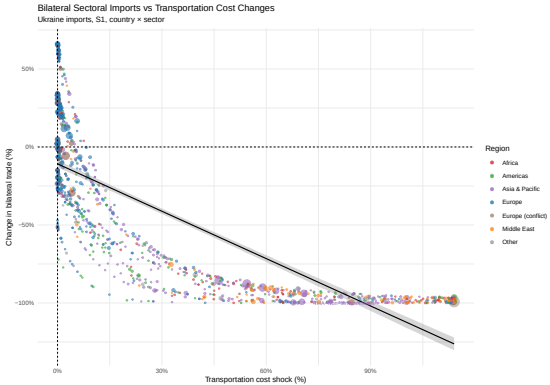
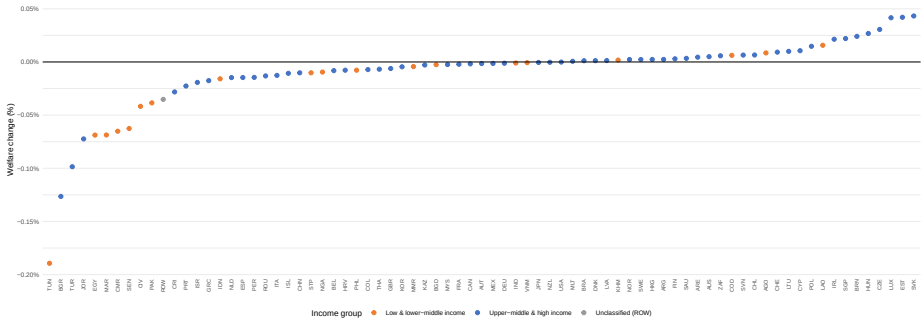


Figure: Imports

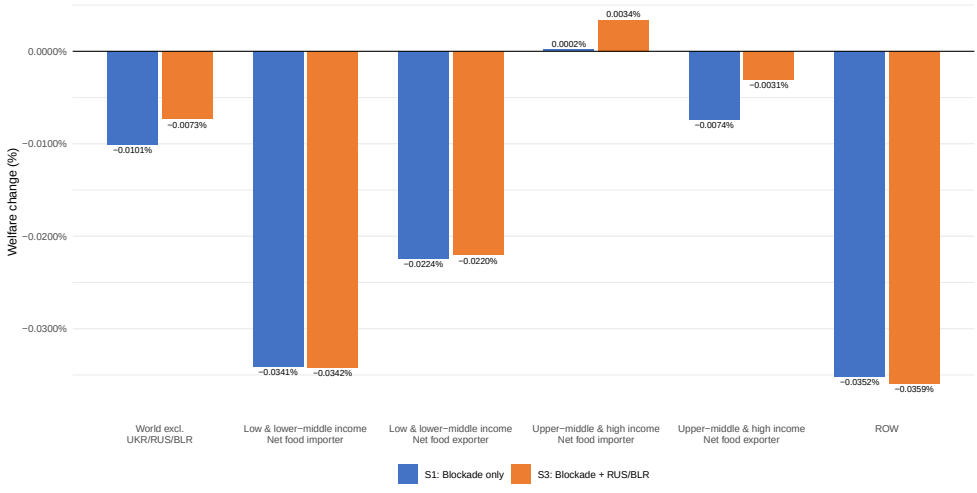
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Model: Welfare Effects for Third Countries



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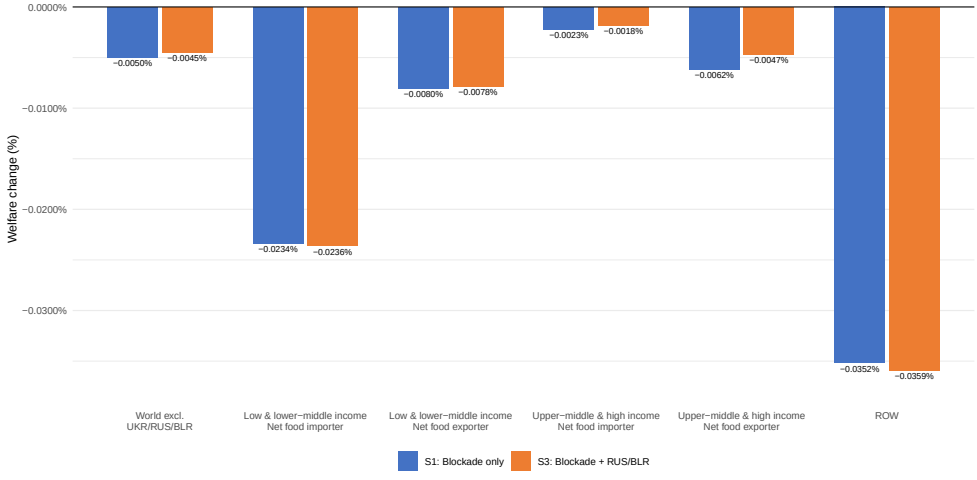
Welfare Cost for the World, Unweighted



Group means unweighted across countries. Income groups: World Bank classification. ROW is a composite and carries no income group. Excluded from every aggregate: UKR, RUS, BLR, TWN.

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Welfare Cost for the World, Weighted



Group means weighted by baseline value added. Income groups: World Bank classification. ROW is a composite and carries no income group. Excluded from every aggregate: UKR, RUS, BLR, TWN.

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Model of International Trade with Transport Modes

- Ricardian trade model: Eaton & Kortum (2002); Caliendo & Parro (2015)
- Discrete transport mode choice: Tolva (2026)
- Details on:
  - Economic environment
  - Technology
  - Transport mode choice
  - Trade flows and gravity
  - General equilibrium
  - Response to a mode-specific shock
  - Welfare and hat algebra

Environment
Technology
Transport
Trade flows
GE
Shock
Welfare

- Empirical implementation:
  - OECD ICIO 2021; 80 economies; 49 industries (27 tradable sectors)
  - Trade shares: BACI dataset from CEPII (Gaulier and Zignago 2010); 2021 year
  - Vessel shares $\pi^{l,s}_{do}$: TDM Ukrainian customs data, 2019–2021 average, by sector $\times$ destination
  - Elasticities $\{\eta^l\}$: estimated from same data
  - Trade elasticities $\{\theta^l\}$: Fontagné, Guimbard & Orefice (2022)
  - Tariffs: Guimbard et al. (2012)
  - Implemented in KITE (Hinz, Mahlkow & Wanner 2025)

Back to Overview

Model: Economic Environment

- N countries (indexed d, o), J sectors (l); labour L_d mobile across sectors within country, immobile across borders; competitive markets

- Cobb-Douglas preferences with fixed consumption shares α_d^l:

$$U_d = \prod_{l=1}^{J} (C_d^l)^{\alpha_d^l}, \qquad \sum_l \alpha_d^l = 1$$

- CES preferences over varieties within sector l

- Household income: $I_d = w_d L_d + D_d$, where D_d is the (fixed) trade balance deficit

- Total absorption of sector l in d (eq. C.6):

$$X_d^l = \alpha_d^l I_d + \sum_k \gamma_d^{l,k} Y_d^k$$

where Y_d^k is output of sector k in d and $\gamma_d^{l,k}$ is the IO coefficient

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Model: Technology

- Cobb-Douglas production with labour and sectoral intermediates (eq. C.4):

$$q_o^l(\omega) = z_o^l(\omega) \cdot \left[l_o^l(\omega)\right]^{\beta_o^l} \cdot \prod_{k=1}^{J} \left[m_o^{k,l}(\omega)\right]^{\gamma_o^{k,l}}, \qquad \beta_o^l + \sum_k \gamma_o^{k,l} = 1$$

- Unit input-bundle cost after cost minimisation (eq. C.5):

$$c_o^l = \Gamma_o^l \, w_o^{\beta_o^l} \prod_{k=1}^{J} \left(P_o^k\right)^{\gamma_o^{k,l}}, \qquad \Gamma_o^l = \left(\beta_o^l\right)^{-\beta_o^l} \prod_k \left(\gamma_o^{k,l}\right)^{-\gamma_o^{k,l}}$$

- Productivity $z_o^l(\omega)$ i.i.d. Fréchet with shape θ^l (trade elasticity) and scale λ_o^l (comparative advantage)

- IO channel: c_o^l depends on all price indices $\{P_o^k\}$ — transport shock in sector l propagates into marginal cost of every downstream sector k

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Model: Transport Mode Choice

- Each bilateral route (d, o) in sector I can be served by M modes; iceberg cost $\tau_{do}^{I,m} \geq 1$ (vessel, truck, railway, aircraft)
- Following Tolva (2026), delivered quantity is a CES aggregate over modes with elasticity $\eta^I > 1$ (eq. C.8):

$$Q_{do}^I = \left[\sum_m (q_{do}^{I,m})^{\frac{\eta^I - 1}{\eta^I}} \right]^{\frac{\eta^I}{\eta^I - 1}}$$

- Effective transport cost = CES cost dual (eq. C.9):

$$\tau_{do}^I = \left[\sum_m (\tau_{do}^{I,m})^{1-\eta^I} \right]^{\frac{1}{1-\eta^I}}$$

- Modal expenditure shares (eq. C.10):

$$\pi_{do}^{I,m} = \left(\frac{\tau_{do}^{I,m}}{\tau_{do}^I} \right)^{1-\eta^I}, \qquad \sum_m \pi_{do}^{I,m} = 1$$

- Limiting cases: $\eta^I \to \infty$ (perfect substitutes: $\tau_{do}^I = \min_m \tau_{do}^{I,m}$); $\eta^I \to 1$ (near-complements: all modes jointly determine cost)
  Hummels & Schaur (2013): ≈ 1.1; Tolva (2026): 1.58–2.31;
  this paper: $\hat{\eta}^X = 2.09$, $\hat{\eta}^M = 1.71$)

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Model: Trade Flows

- With Fréchet productivity and lowest-cost sourcing, share of d's sector-l expenditure sourced from o (eq. C.14):

$$\pi^{l}_{do} = \frac{\lambda^{l}_{o}\left(\tau^{l}_{do}\, c^{l}_{o}\right)^{-\theta^{l}}}{\Phi^{l}_{d}}, \qquad \Phi^{l}_{d} = \sum_{h} \lambda^{l}_{h}\left(\tau^{l}_{dh}\, c^{l}_{h}\right)^{-\theta^{l}}$$

- Sectoral price index: $P^{l}_{d} = A^{l}\left(\Phi^{l}_{d}\right)^{-1/\theta^{l}}$

- Goods-market clearing (eq. C.7): $Y^{l}_{o} = \sum_{d} \pi^{l}_{do}\, X^{l}_{d}$

- **Bilateral-flow elasticity to a mode-specific shock** (eq. C.13) — the key testable implication:

$$\frac{\partial \ln X^{l}_{do}}{\partial \ln \tau^{l,s}_{do}} = -\theta^{l}\, \pi^{l,s}_{do}\,(1 - \pi^{l}_{do})$$

  Sea-intensive routes ($\pi^{l,s}_{do}$ large) respond most strongly. The shift-share estimates test this directly.

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Model: Response to the Blockade Shock

- Port blockade = proportional increase $\hat{\tau}_{do}^{l,s}$ in cost of vessel mode *s*, all other modes unchanged

- Pass-through to effective route cost (eq. C.11):

$$\hat{\tau}_{do}^{l} = \left[1 + \left(\hat{\tau}_{do}^{l,s}\right)^{1-\eta^{l}} \pi_{do}^{l,s}\right]^{\frac{1}{1-\eta^{l}}}$$

- Three key features:
  - Pass-through depends only on $\pi_{do}^{l,s}$ and η^{l} — level of mode costs not needed, so counterfactual runs directly from observed modal shares
  - Substitution *always attenuates*: $1 < \hat{\tau}_{do}^{l} < \hat{\tau}_{do}^{l,s}$
  - Attenuation weakest where blockade bites hardest: routes with $\pi_{do}^{l,s} \approx 1$ and $\eta^{l} \approx 1$ (bulk agriculture and metals)

- For simultaneous shocks to multiple modes (eq. C.12):

$$\mathrm{d}\ln \tau_{do}^{l} = \sum_{m} \pi_{do}^{l,m}\, \mathrm{d}\ln \tau_{do}^{l,m}$$

  Combined effect is a share-weighted sum of individual mode shocks

Model: Equilibrium in Changes (Hat Algebra)

- Solve model in changes $\hat{x} \equiv x'/x$ (Dekle, Eaton & Kortum 2007) — requires only baseline trade shares, IO coefficients, elasticities

- System (eqs. C.15–C.21): given $\hat{\tau}^{l,s}_{do}$, solve for $\{\hat{w}_o, \hat{P}^l_d, \hat{\pi}^{ll'}_{do}, \hat{l}'_d, \hat{X}^{l'}_d, \hat{Y}^{l'}_o\}$

$$\hat{\tau}^l_{do} = \left[1 + \left(\hat{\tau}^{l,s}_{do}\right)^{1-\eta^l} \pi^{l,s}_{do}\right]^{1/(1-\eta^l)} \qquad \text{(effective cost change)}$$

$$\hat{P}^l_d = \left[\sum_o \pi^l_{do} \left(\hat{\tau}^l_{do} \hat{c}^l_o\right)^{-\theta^l}\right]^{-1/\theta^l} \qquad \text{(price index change)}$$

$$\pi^{ll'}_{do} = \pi^l_{do} \left(\hat{\tau}^l_{do} \hat{c}^l_o / \hat{P}^l_d\right)^{-\theta^l} \qquad \text{(new trade shares)}$$

- Wages $\{\hat{w}_o\}$ clear labour markets globally; one wage normalised as numéraire

- Algorithm: outer loop on wages; inner loop on $\{\hat{c}^l_o, \hat{P}^l_d\}$ to fixed point (KITE: tolerance 10^{-4}, damping $\nu = 0.01$)

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Model: Welfare

- Real income change = welfare measure (eq. C.22):

$$\hat{W}_d = \frac{\hat{I}_d}{\prod_l (\hat{P}^l_d)^{\alpha^l_d}}$$

Back to model details Back to welfare results

References I

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